Public Opinion Formation on Social Media in a Big Data Perspective

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Measuring Political Homophily and Cross-cutting Agreement

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Abstract

The establishment and constant development of social media technologies over the last two decades have left media scholars with a burning desire to understand their contribution to the formation of public opinion and its political consequences. At this very moment it is undeniable that public opinion fuelled by social media is a force to be reckoned with. At the same time, the complex information flows and communication practices on social media make it difficult to predict how public opinion will form. Research into how information and opinions are shared has created concerns that some parts of the public are becoming increasingly politically homogenous and polarized due to social media.

This thesis project suggests a new framework to evaluate the function of public opinion, specifically in relation to the opportunities offered by social media. The framework is inclusive and conflates concepts that are usually considered separate within the field of media studies e.g. opinion polling and deliberation. It is a descriptive framework that highlights advantages and weaknesses for certain instances of public opinion. The framework is used to inform the development of computational methods that can be used to gauge public opinion with respect to political homophily and polarization. These methods rely on automatically calculating the cross-cutting agreement, i.e. how much agreement there is between people with opposing political affiliations, as they interact in public social media discussions. They are developed as universal methods to enable public opinion to be measured based on how politically homogenous the users who react to and share a piece of information are and how well political oppositions in the comment threads are able to reach agreement, in combination with topics and sentiments. The methods are tested on a large cross-section of public Danish Facebook pages related to everything from local fitness clubs to government pages and news media organization.

Results show that high levels of political homophily and disagreement that are likely to cause polarization are highly dependent on context. Overall polarization does not appear to be increasing over a period of five years, except if moderated by certain other factors of which discussion topics related to refugees and immigration is one of the strongest. The results are furthermore an indicator that the methods developed can be used to effectively evaluate public opinion with respect to homophily and polarization. Since the methods are computational, the process is easily automated and can be used to create

tools that can deliver increased transparency in public opinion formation as it unfolds on social media platforms.

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Introduction

Social Media, Big Data and The Online Public Sphere – New Directions for the Formation, Function and Reaping of Public Opinion

Social media technologies have taken a hold of the world over the last couple of decades. Evolving from quaint curiosities into a dominating force for the creation and spread of public opinion. There will always be people who shun or consciously opt out of using new technologies, but social media have become so ubiquitous that few people around the globe are able to not take account of their existence at all. As such, democratic societies for which an informed citizenry is preferable to one that is rife with ignorance and apathy, social media has become an unavoidable element in the sphere of public opinion.

Since the Enlightenment (from a European perspective), the efficacy of public opinion has been viewed as an important aspect of healthy democracies (e.g. Rousseau, 2002 [1762]). Having public opinion be an integrated part of any democratic society seems to be congruent with the idea of rule by the people, rather than the public opinion being second to an all-powerful governmental body. Institutionalized voting, elections and referendums are found in most democratic societies in order to guarantee the influence that the public has on their government. Whether or not current voting practices best serve the electorate, the fostering of public opinion is an important aspect in providing citizens with best conditions for making informed decisions. And even so, there is little consensus about how to treat public opinion: how reliable or fickle is the public's opinion really? Should experts bear the main responsibility of informing and setting up choices for the public to choose between or is the public capable of reaching a direction on its own? How much of the public's opinion should be taken at face value and how much should it be subject to procedural or rational norms? Those are some of the questions which form the background for this project, though seeking to fully answer them is outside the scope of this thesis. This project builds on the premise that increased and effective communication among citizens as well as between citizens and governing bodies can help improve the quality of public opinion and overall satisfaction with democratic rule. However, the project does not rely on predetermined normative principles for evaluating the quality of public opinion per se. Rather, public opinion as a communicative force is examined in terms of the strength and weaknesses that manifest depending on how it is framed, formed and gauged. The varying functions of public opinion is later presented in a descriptive framework entitled: the triaxial model.

With his seminal work on the public sphere, Jürgen Habermas (1989 [1962]) initiated a discussion, one that is still ongoing today, about public opinion and its function in relation to media technologies and political institutions in mass democracies. Discussions related to the role of media technologies in fostering public opinion, what is often referred to as the public sphere perspective, is likely to continue as long as technologies and communication practices are changing (Lunt & Livingstone, 2013). New possibilities and potential debilities of changing media technologies have to be constantly considered as change is occurring if democratic rule is to be enriched rather than diminished. Of course, the functioning of any society relies on many aspects such as social structures, political economy, infrastructure, education etc., however it is assumed that the use of media technologies and its impact on public opinion have an independent role to play, for better or worse.

As with any new media technology, concerns about social media's negative impact on public opinion have taken the stage; or rather, what the discussion is actually centred on is whether the potential deficits of social media outweigh their potential benefits. Were radio and television increasingly effective ways to inform the masses, or were they dumbing down, politically pacifying and de-socializing people? Specific media technologies and formats all offer their own unique features that can either help foster an informed citizenry or risk dividing people and making them increasingly distrustful of media. Misinformation and disinformation have found new life with social media, and social psychological biases and algorithmic filtering mechanism have been shown to greatly affect the way information is found, consumed and shared; all of which has been deemed potentially dangerous for politics in democratic societies. The role social media play in generating increased political polarization has become one of the primary focal points for studying social media and public opinion. Whether such polarization is due to the intentional dissemination of disinformation, structural, commercial, social, personal, algorithmic or even journalistic biases, there is evidence that all might have been impacted based on the way social media have changed the way information is curated.

Social media have taken on a role of their own in society, not just as social networking tools, but also as part of a larger category of technologies, which can best be termed online digital media. Social media are purely digital and connected to the global internet[1]. As such, social media have become a source of Big Data and is ultimately dependent on the commercial value of extracting insights from said data (Zuboff, 2018). However, the extraction of information from such large amounts of behavioural data is not limited to commercial use. Social media offer spaces for debate as well as easy ways to plan dinner parties. The exchange of opinions about everything from designerware to international politics are taking place in myriads of ways. Digital traces left behind from every single interaction/transaction between users and content, and among the users themselves, on social media platforms, provide insights into the processes behind and output of public opinion formation. Such insights can be used to further our understanding of public opinion formation but can also be repurposed and shared back to the users in an effort to make the process of opinion formation more transparent. This thesis project offers a theoretical framework as well as a specific set of methods for analysing political debates in public spaces on social media with respect to political homophily and the potential for cross-cutting agreement.

This thesis will argue a new way to operationalise the concept of public opinion in the public sphere tradition with respect to the communicative potentials of social media, using Facebook as the main example. The formation of public opinion is related to social media specific characteristics and how they impact people's ability to find, share and discuss politically relevant information. The concept of public opinion is coupled directly to methods for large-scale measuring of behaviour related to political polarization (or de-polarization) by focusing on users' ability to interact with people whom they do not politically agree with. The methods are tested on a large cross-section of public forums representing the Danish public on Facebook and used to show the degree to which political polarization exists and evolves over time on the platform as well as the degree to which such polarization depends on various contexts. The theoretical framework and methods are developed for social media in general, but the empirical case is limited to Facebook in Denmark. This imposes a bias on the results such that the usefulness of the

[1] The internet as it is known today is potentially global, but not de facto global as some countries have been successful in denying access to a huge part of their population (e.g. China, Syria, Saudi Arabia).

methods might be constrained by communicative behaviour that is specific to Danish culture. However, the research design for studying homophily and polarization aims at a general rather than specific frame when it comes to topics, types of pages, party politics and other categories. While not all countries have a very high degree of political communication on a single social media platform, as is the case with Facebook in Denmark, at least a few dozen other democratic countries do have similar levels of social media use (measured as how many percent of the population are active[2]). Furthermore, in order to show the potential for universal applicability if the methods in this project, some exploration is carried out on data from Facebook in New Zealand. A full comparative study of several countries would be outside the scope of the project. Focus is on developing and documenting a fairly complex set of computational techniques and then testing them by analysing the main patterns from Facebook in Denmark. While the methods show potential for universal applicability, the patterns pertaining to political homophily and polarization that are ultimately extracted apply only to Facebook in Denmark.

The final argument is that methods, such as those developed for this project to measure and study political agreement/disagreement in public spaces on social media, can, due to them being easily automatable and relying on already existing data flows, be repurposed and used to let the public know itself as an enriched data-public. It offers a way to positively intervene in spaces that are dominated by obscurity and commercially motivated extraction of data.

Outline of Thesis

The academic contribution of this thesis project is to propose a new way to view the concept of public opinion in relation to social media that is directly coupled with methods to automatically measure and review the opinion formation process, specifically focusing on behaviour related to political polarization.

[2] https://www.pewresearch.org/global/2018/06/19/social-media-use-continues-to-rise-in-developing-countries-but-plateaus-across-developed-ones/

In order to understand public opinion formation on social media it is necessary to start with a thorough review of theoretical discussions surrounding public opinion. The concept of public opinion itself is quite fuzzy. For this reason, public opinion is traced specifically through the lens of the public sphere tradition, which has become one of the most popular areas for media studies related to political communication (Dahlgren, 2009, 9). Chapter 1 sets up the general theoretical boundaries for the concept of the public and public opinion. Publicness relates to both spaces and people, and an intuitive distinction such as the one between private and public becomes increasingly blurry with social media. The chapter discusses the relation between publics and audiences in order to make clear when a body of people can effectively contribute to the formation of public opinion.

The study of public sphere discussions centred on online digital media and social media have been a popular endeavour over the last two decades, and a variety of new concepts for understanding public opinion and media technologies have been introduced in the literature. An overall framework, coined *the triaxial public opinion model,* is proposed in order to frame earlier concepts of the public. The model considers how previous concepts view the function of the public on three different axes, which will not be described in detail here: 1) Voice versus aggregation, 2) consensus vs agonism, 3) engagement versus ignorance. The purpose of the model is not to create an exact map that fully explains all previous concepts of the public, but to create an overall frame to collect and highlight contrasts and similarities between the concepts. The lasts parts of the chapter begin by tracing concepts related to public opinion starting with Habermas' original critique of the changing structures of the public sphere. After Habermas, a few additional concepts are discussed including distinctions between formal and informal publics as well as polled publics and mini publics.

Chapter 2 takes a step back in order to review how politically relevant content is published, shared and consumed on social media. The first part seeks to highlight the major characteristics of social media within the medium theory tradition; what makes online digital media and social media distinct from other mediated forms of communication. The focus is on three often studied aspects of online digital media: 1) media convergence, 2) user interaction, 3) mediatization and personalization. Next, the chapter goes into detail about how information flows and is received in the network structures of social media. Two specific theoretical concepts are used to frame social media-specific communication practices related to political polarization as an effect of content sharing and participation in public discussions: *curated flows* and *expression effects*. Information flows can be seen as a combination of five types of curation: personal, social, strategic, journalistic and algorithmic; and user interaction, both between users and content as well as among users, can be viewed not simply as a transmission of a messages to other people, but also as expression effects that impact the senders themselves regardless of whether other users react or even receives them.

Since public opinion relies on some instance of people coming together to form a public, the chapter considers how people connect and form meaningful, though potentially short-lived, gatherings on social media. Opinion formation relies on cross-cutting flows of information through social networks that can be endlessly reconfigured; thus, it is important to reflect on the relevance that short-lived and somewhat ephemeral gatherings of social media users have. The rest of the chapter mirrors the last part of the previous chapter by reviewing a selection of theoretical concepts related to public opinion in light of the triaxial model, but in this chapter the focus is on conceptions of the public that have been specifically used or created to analyse social media. The concepts being reviewed are counter publics, issue publics, networked publics, data publics, affective publics and acclamation publics.

Public opinion for this project is viewed through the lens of political agreement/disagreement between people in the public; one of the reasons being that it is strongly related to the potential polarization of societies. Chapter 3 outlines previous findings and conceptualizations specifically related to political engagement in public online forums, the connection between political preferences and media consumption and political polarization with respect to political homophily, filter bubbles and cross-cutting agreement. The chapter begins with a discussion of public social media forums as spaces for political debate. Because of the sometimes ephemeral character of social media publics and the fact that politically relevant discussions can occur in spaces that are not overtly set up for political debate, it is necessary to frame what political engagement means on social media. Next, the chapter addresses how curation practices can be framed in relation to the political preferences of individual users. Political engagement with content and other users is explained with four modes: 1) the intentional engagement with political content and people that are politically similar to the user herself, 2) the unintentional engagement with the politically similar (guided by less visible biases), 3) the intentional engagement with the politically *dis*similar and 4) the unintentional engagement with the politically dissimilar. Additionally, the complexities regarding the political polarization of the public are discussed with respect to many divergent and sometimes contrasting findings that have come from studies into the actual effects of engagement with politically similar/dissimilar content as well as agreement/disagreement in discussions among people with different dispositions and political preferences. The chapter wraps up the theoretical framework by outlining its use in the empirical study.

Chapter 4 introduces the methodological framework for the project. As mentioned earlier, the methods developed for this thesis have a two-fold purpose, both to investigate public opinion formation related to political polarization and to serve as an example of data analysis can be automated and made into tools that can help make public opinion formation more transparent to the public itself. For this reason, the methods are computational and Big Data-oriented, meaning they are custom-made to handle large data streams and extract very specific patterns from them. There is no previous research using the exact same set of methods, but the general approach is informed by the *social analytics* framework (Stieglitz, Mirbabaie, Ross & Neuberger, 2018).

The empirical data that is the main interest of this project is the behavioural data collected from a large cross-section of Danish public Facebook pages; this includes the content published, who is reacting to and/or commenting on it, when each interaction occurs and how users interact with each other. In total more than a billion likes, comments, posts and replies collected from over 10.000 public pages. The study of public opinion is centred on the political preferences of the users. Thus, part of the methodology is a survey of users and their political affiliation, which is used to design methods that can be used to predict the political affiliation of all users in the Danish public. Having attained the political preferences of the users, the next step involves developing techniques to calculate political homophily and political agreement/disagreement based on how users interact with content and each other. Part of the social analytics framework involves using the content and some contextual features to account for behavioural patterns at a more fine-grained level. Thus, the last set of methods have the purpose of allowing behaviour to be studied based on the type of space in which it takes place, the topics being discussed and the sentiment of the language used.

Chapter 5 has a singular purpose: to show that users' political preferences can be predicted to an acceptable degree of certainty based on their engagement with politicians and political parties on Facebook. This is done by doing a survey study in which respondents state which political party they voted for in the two last national elections as well as who they would vote for at the time of the survey. Each individual respondent has their answers connected to their Facebook profile. Their Facebook behavioural history is then used to train a machine learning classifier to predict their voting intention, which yields an accuracy of 70% for the multiparty level and 99% for the left/right scale.

Chapter 6 builds directly on top of the results obtained in the previous chapter. Assuming that previous behaviour on political pages is a strong indicator of political preference, this chapter proposes a series of methods for calculating the degree of political homophily and agreement/disagreement in multiple steps of communication. Specifically, it seeks to determine how politically homogenous the participants in a given discussion are and how much agreement there is based on users' reactions to the published content as well as their continuing interactions among each other in the comment section. Since no ground truth can be obtained against which to test the reliability of the calculations, it is instead tested against a few common-sense expectations e.g. political disagreement should on average be noticeably higher on discussions that have a clear political angle compared to those initially focused on other matters.

Chapter 7 presents the procedures used to divide pages into categories based on the types of content they focus on and the model developed to sort discussions into topics based on the actual content in the initial Facebook post around which comments and reactions are made. Lastly a machine learning model is developed to determine the degree to which posts and comments use harsh language or not.

In chapter 8 all the main results are presented. They show the development of political homophily and agreement/disagreement in the Danish public over time as well as its distribution in relation to spaces, topics and sentiments. While the public overall does not appear to become increasingly homogenous or polarized over time, there are some clear exceptions depending on the context. As such topics related to refugees and immigration and spaces dominated by supporters of the mainstream populist party elicit much higher levels of political homophily that are steadily increasing over time compared to other topics and spaces. The same can be observed for the topic refugees and immigration political disagreement, especially in combination with use of harsh language. Some additional patterns are revealed with the overall conclusion that social media does not appear to, in itself, be the cause of polarization, instead any such trend seem to be very dependent on specific contexts.

Chapter 9 is an in-depth discussion of the methods and the results in light of the theoretical framework. Focus is on how the methods developed and tested in the project can be used to enhance the tools that people have when engaging with content and other users on social media platforms. The results show that patterns pertaining to political homophily and agreement/disagreement can be ascertained on a micro level, which could potentially be done as the opinion formation is unfolding. Such techniques can be used to make public opinion more transparent e.g. by highlighting comments that are eliciting cross-cutting agreement or whole discussions that are becoming increasingly homogenous. Public opinion in this project is not viewed through the lens of a predetermined set of normative principles, different configurations of the public have advantages and weaknesses. However, improving the transparency of opinion formation processes as they occur across obscure networks of affective data publics will at least provide the public itself with better knowledge and increased agency.

Chapter 1. The Public as an Opinion Forming Body

The Interest in Public Opinion

Public opinion is of general interest because it represents the collective thoughts of more than a mere individual or small group of people. It shapes the norms that people live by. Knowing the opinion of the public means knowing what people want, or at least what a great mass of people leans toward. It is of interest to producers, employers, manufacturers, lawmakers and society at large, anyone who are responsible for making decisions that will affect the boundary conditions of significantly large groups of people.

Public opinion research does not adhere to a strictly defined field or discipline. It is one of the fuzzier terms used in academic research (Donsbach & Traugott, 2008). It spans the areas of political science, philosophy, law, communication, marketing and more, however there is no doubt that it has become one of the most central topics in media research. Still the term public opinion is often used in a broad sense to denote the public in general, or what a significant part of the public, thinks about something pertaining to any category including science, religion, consumer products, politics etc. Especially in democratic societies, being mindful of public opinion functions as a "self-organizing" principle for social and civic relations (Calhoun, 2010, 304).

This thesis is primarily concerned with public opinion in relation to politics and especially the role of media technologies as a facilitator of opinion formation. Public opinion as a relevant term in politics has existed in some version in Western societies as far back as Ancient Greece, however it was not coined until the Enlightenment (Herbst, 2015). In the same context it should be mentioned that public opinion in politics is inextricably linked to democracy as a form of governance, or as Strömbäck remarks, "…public opinion is the main currency in democracies" (2012, 2). In the case of non-democratic governments public opinion might be necessary to take into account, but, as

Machiavelli (1513/1992) has noted, it is considered something to be controlled rather than fostered and is not used as a basis for decision-making. Some would claim that there is a lot of control over the formation of public opinion, even in modern, liberal democracies (e.g. Habermas, 1962/1989, Herman & Chomsky, 1988), still the general idea is for public opinion to represent the wishes of the people and directly influence legislation, policy-making and overall organization of society (Aalberg & Curran, 2011). Thus, almost all Western, post-Enlightenment scholars have been concerned with the practical and theoretical principles behind the best possible implementation of public opinion as the basis for sustaining a healthy democracy. It is within this scholarly debate, which has run alongside the advancement of communication technologies, that the conceptualization of the public as an opinion forming body is to be sought.

Outer conceptual boundaries: Multitudes and Publicness

Two concerns must be addressed before the concept of public opinion can gradually be explored and put to use: 1) public opinion as multitude and singularity, and 2) public as different from non-public. These concerns will be examined in greater detail throughout the chapter, but they need to be addressed on a general level in order to have a minimal sense of the theoretical and practical limits pertaining to the term public opinion.

When speaking of 'the public', it can refer to both people and space (Tarta, 2014, 2), and the right configurations of both are necessary for the formation of public opinion. A public as people is the simplest to conceive of. It needs to include more than two people and those people need to 'come together' in some broad sense (Childs, 1965, 13). The most important aspect to mind here is how the function of coming together can be fairly abstract. The public can take form in a physical assembly such as a town meeting or a parliamentary debate, but it can also be facilitated through more asynchronous and distributed means of communication such as the writing and reading of newspapers or the creating and accessing of websites. This idea builds on the notion of imagined communities (Anderson, 1983), which theorizes the coming together of a nation without the people who make up the nation ever meeting in person. Although, being in the same room or reading the same newspaper does not make two people part of a public. It is necessary to flesh the differences between a collection of individuals and a public, and as such it will be discussed in detail in this section and the following.

When is public opinion singular? One line of discussion focuses on the distinction between 'the public' and 'a (specific) public'. However, it is possible to assume that the concept of 'the public' is mostly used as a semantic signifier to address a fluid constellation wherein the public can be viewed as literally everyone, a great many, a majority, a constituency, a representative selection etc. (Sartori, 1987, 22). This thesis is focused on public opinion as the product of 'a public', a specific gathering of people, and thus it will be assumed that the public is always potentially plural (Tarta, 2014, 26). There can be many publics each forming their own collective opinion, however the opinion pertaining to a certain public must be minimally singular. Minimally singular in this sense means that depending on how the opinion was formed, it can be either utterly simple or very complex, but it must be a collection of thoughts that represents a funnelling of individual opinions into something that can be enunciated as the collective opinion pertaining to the whole of a body of people. This is also a way of saying that public opinion on a practical level need to have some direction; it is typically in response to some common concern (Dewey, 1927, 11), or put a different way, it reflects the transformation of a multitude of opinion into 'uniformly effective power' (Tönnies, 1887/1957, 221). Depending on where it is located in the following framework, public opinion can have many characteristics; it can be complex, shallow, exact, fuzzy, representative etc., but it must have attained the status of something more than a collection in which individuals can be identified only by their own peculiar opinions. Even though public opinion is most often referred to in cases where people have come together or been collected in some way, such as a protest or an opinion survey, with there being some direction to the opinion, this thesis will not assume that people are always conscious of the direction or even of the fact that they are a part of the formation of public opinion. Some of these concerns will be reiterated later in the chapter.

The public as space relates to the question of whether a certain place, either physical or virtual, can actually be considered public. The scholarly debate on this issue typically follows two streams: 1) the distinction between private and public lives of individuals (e.g. Goffman, 1959; Meyrowitz, 1986; Papacharissi, 2002) and 2) the political-economy perspective of whether the space represents public or private interests in terms of ownership, control and access etc. (e.g. Valtysson, 2012; Fuchs, 2014; Hendricks & Hansen, 2014), which is what Dahlgren (2005) has referred to as the structural dimension of the public sphere. While the latter plays an important part for the conditions of public life it does not need to be conceptualized explicitly in order to create a framework for the practical function of public opinion and thus will be given less attention in this thesis.

When is something considered public or non-public? In the most common sense, publicness can be attributed to that which is generally made open and visible in opposition to safeguarded and hidden (Splichal, 2012a). An expansion of this distinction can be made into a normative (Kantian) set of principles pertaining to *visibility, accessibility* and *publicity* (Tarta, 2014, 21-22). In this sense, the condition of publicness requires a space that is accessible and, at least to the highest possible degree, visible to all people. Publicity refers to the Kantian idea, which describes the condition of making the same information available to all involved parties (Clinger, 2017, 395), and not the more modern conception related to promotion and advertising. Publicity is different from accessibility as it requires not only the space of opinion to be accessible to as many people as possible, instead the space itself should be structured to make sharing of ideas within it as easy as possible among all who have vested interests. Thus, the public as space should try to accommodate as much visibility, accessibility and publicity as possible.

The other popular distinction in conceptualizing the public as space is between public and private. Public and private are most of the time thought of as separate, but also permeable to each other. A private home is physically separated from the public agora, but private concerns might be voiced in a public forum. There is some confusion in the literature due to overlapping meanings of the words *private* and *personal*, which are often used interchangeably. However, in one of the most famous distinctions between public and private sphere, private and personal are very different (Habermas, 1962/1989). In Habermas' version only private concerns, which include economics, trade relations and exchange of commodities, should be permeable to the political public, whereas personal affairs including domestic relations, family, hobbies, recreation etc. are preferably not relevant in public deliberations. Many adaptations of Habermas' original concepts of public and private spheres have conflated the private and the personal (Jensen, 2010, 69). This thesis will build on the more recent, and more commonly used, distinction between personal/private and public rather than the strict Habermasian terminology.

The evolution of social structures and media technologies has caused significant changes in the relation between public and private spheres. With the proliferation of televised content at the turn of the millennium the connection to public life became increasingly situated in the home environment, sitting in front of the screen (Putnam, 2000), while the internet made a whole range of public activities possible from inside the physical private sphere (Papacharissi, 2010). This blurring of the boundaries between public matters, personal spaces, private interest and intimate affairs makes publicness less dependent on any one type of space, physical or virtual. Instead, the condition of publicness should apply to all acts where a high degree of visibility, accessibility and publicity is sought. In this sense, the condition of publicness is very much related to the 'performance of publicness' (Matheson, 2018). While traditional means of entering into the public, such as attending meetings or protest events are still widely pursued, the performance of publicness has become expanded. People can fluidly attempt to negotiate the degree of visibility, accessibility and publicity while engaging in communication activities from within a space that is primarily[3] private (Papacharissi, 2010, 138-139).

The Enactment and Construction of Publics

At this stage it is necessary to address what qualifies as a public. One of the usual lines to draw in media research is that between audience and public, a distinction that has gained attention with the growing dominance of mass media. Audiences have typically been considered passive and only able to gain expression as a pure aggregate through ratings and similar measurements, whereas publics actively direct attention, typically through some kind of interaction or by actively coming together (Dayan, 2001). This thesis follows the same train of thought but seeks to be as inclusive as possible while still drawing a line. In this sense it is important to recognize that the line between audience and public has always been hard to define and has become even blurrier with online digital media (Baym

[3] It can be argued that issues pertaining to Big Data, lack of digital privacy legislation, the right to be forgotten and increased surveillance makes this primarily private space, originally conceived by Papacharissi, somewhat illusory.

& boyd, 2012, 322). All collective constructs such as nations, markets, crowds, audiences and publics, whatever term is used, are, after all, composed of the same people (Livingstone, 2005). Thus, audiences are able to morph into publics by drawing on the mutual recognition of being receivers of the same information and engaging in activities that are socially visible, in contrast to private and obscured (Dahlgren, 2009, 73). It is this transition to socially visible activities that constitutes the construction of a public, distinct from simply an audience. This is akin to saying that the construction of a public requires a two-step flow (from the perspective of Katz and Lazarsfeld (1955)), where people first interact with media content[4] and then interact with each other. Another way of saying this is that the public must have a performative dimension where communicative acts are carried out by the members of the very public they represent (Dayan, 2005).

It should be recognized that the first interactive step (between audience and media content) is not only determined by individuals and their rational free choices in a marketplace of ideas but are being co-constructed by media organizations and political entities. Politicians will sometimes want to address their core constituency and media organizations their main readership/viewership, thereby seeking to influence the construction of a public and give it in a certain direction (Eldridge, Garcia-Carratero & Broersma, 2019). This co-construction is most often a tactic where powerful actors try to maintain the attention and favour of an audience/constituency (Ross, Fountaine & Comrie, 2015), but it still has an effect on how the public is potentially enacted in the second interaction step (among citizens). Furthermore, the continuous interaction between media and audience can serve as a kind of backdrop for the public by maintaining and organizing discourses. The circulation of texts is critical, and it is possible to regard it as the primary condition for the public to be able to realize itself (Warner, 2002, 50). However, even though a large potential public is gathered through discursive flows, it is useful to only consider it a public, and not simply an audience, when it gains some expression or direction. This so-called expression can come about in multiple ways: by people actively meeting and/or seeking publicity as a congregation with a specific direction, or by people being brought together purposely by third-party intermediaries.

[4] Dahlgren (1995) justifies calling the first step 'interactive' by stressing the cognitive and interpretative processes required of the individual viewer/reader.

This thesis follows the idea that an audience, which is identified only by its passive media consumption wherein each audience member mainly recognizes her own particular interests with no effort made by any party to actively bring other members together, does not qualify as a public. However, a critical difference is that this thesis diverges somewhat from previous trends by recognizing all means that bring people together, even if very little interaction takes place. This is where opinion polls and even television ratings can be thought of as the construction of a public. Television ratings as an example can have political relevance if they are unusually high during the showing of a critical documentary, thus subtly suggesting that the opinions brought forth are of particular interest. The transition from audience to public lies in recognizing this particularly high ratings level and making it known. In the same line, opinion polling takes up very little space in media research related to the public sphere perspective. It is often relegated to the field of political science, to its own sub-field or viewed only as a specific technique that media organizations sometimes employ (Traugott, 2012). One reason to at least consider the possible value of a public expressed through an opinion poll is that it very closely resembles the main expression of the national public in democracies, that of the election process (Gallup, 1971, 220).

The difficulty in engaging with the concept of the public and its political relevance follows two contrasting views about the main criterion for a public: 1) that members are visible to each other and interacting or deliberating openly (Splichal, 1999); versus 2) that the opinion of people is surmised and attains a clear form such as through the technical process of opinion polling or other means of aggregating or summarizing. The latter view is built on the postulate that if public opinion is not carefully measured then it does not really exist (Osborne & Rose, 1999, 387). The latter focuses on measuring public opinion while the former is concerned with publicly fostering opinion. These two contrasting views can be traced through traditional enactments of publics. Bryce (1888/1995) envisioned that a public could be realized through one of four organs: 1) the Press, 2) elections, 3) public meetings and 4) citizen associations. The Press and elections can loosely be considered to follow aggregative audience logic while public meetings and citizen associations are small-scale and based on ideas about deliberation and public engagement.

Instead of viewing the aggregative mode as a false, anonymous public and publics that require open deliberation as an indeterminate phantom public, the functions of deliberation and aggregation are put on opposite sides of a spectrum that can contain many different conceptions of the public, each with their own strengths and weaknesses. One might feel tempted to post the question: 'why even bother conceptualizing public opinion if the final form is so inclusive? Is not everything a public then?' The answer is 'no', there are still important distinctions between random masses of people and those that come together with 'uniformly effective power', which will be touched upon in the following sections. Also, one of the primary motivations for employing this more inclusive view of the construction and enactment of publics is that online digital media, which is a main focus in this thesis, offer new conflations of deliberation and aggregation practices that impact the formation of public opinion. Before the popularization of the internet people were, to a greater extent, split between either passively consuming information or engaging in political activities that required some effort such as attending a protest or a town meeting, writing letters to the editor, contacting local politicians and initiating dialogues with other citizens. The online and the digital also inject new problems into the aforementioned debate about measuring public opinion and publicly fostering opinion. People are no longer split into passive mass audiences whose opinion can only be obtained through elections, polls and surveys and small, actively deliberating congregations. Online digital media provide a space where socially visible interaction does actually take place but requires much less effort; and where the sharing, endorsing and discussion of political information can be more easily aggregated.

Introducing the Triaxial Model

Because of the fuzziness and wide-ranging implications of public opinion as a concept, this thesis finds it necessary to lay out a guiding framework through which different aspects of public opinion are viewed in the rest of this chapter. The public sphere tradition in the field of media studies has brought many theoretical perspectives on the function of the public, both normative and descriptive. This chapter introduces the *triaxial model,* which brings together six key terms from theories of public opinion and the interrelation between them by placing them across from each other on three separate axes. The model should not be viewed as an exact schematic for grasping all major theoretical issues related to public opinion, rather it is a lens through which to view various conceptions of the public that can facilitate the analysis of the function of public opinion on social media. It is necessary in order to establish how social media platforms can enable new forms of public opinion, not possible before the Internet. Albeit, many attempts have been made to do just that. The unique contribution of the triaxial model is the collection of previous literature into a unifying lens that is directly connected to the way Big Data methods can be employed to reveal both how opinion is formed as well as how it can be gauged, measured and used. The triaxial model is illustrated in Fig. 1.0, however the complete significance of the model will only be apparent at the end of the chapter. The following sections will describe each of the axes in the model, and the rest of the chapter will begin the review of concepts from the public sphere tradition. The triaxial model is used to put the concepts in perspective.

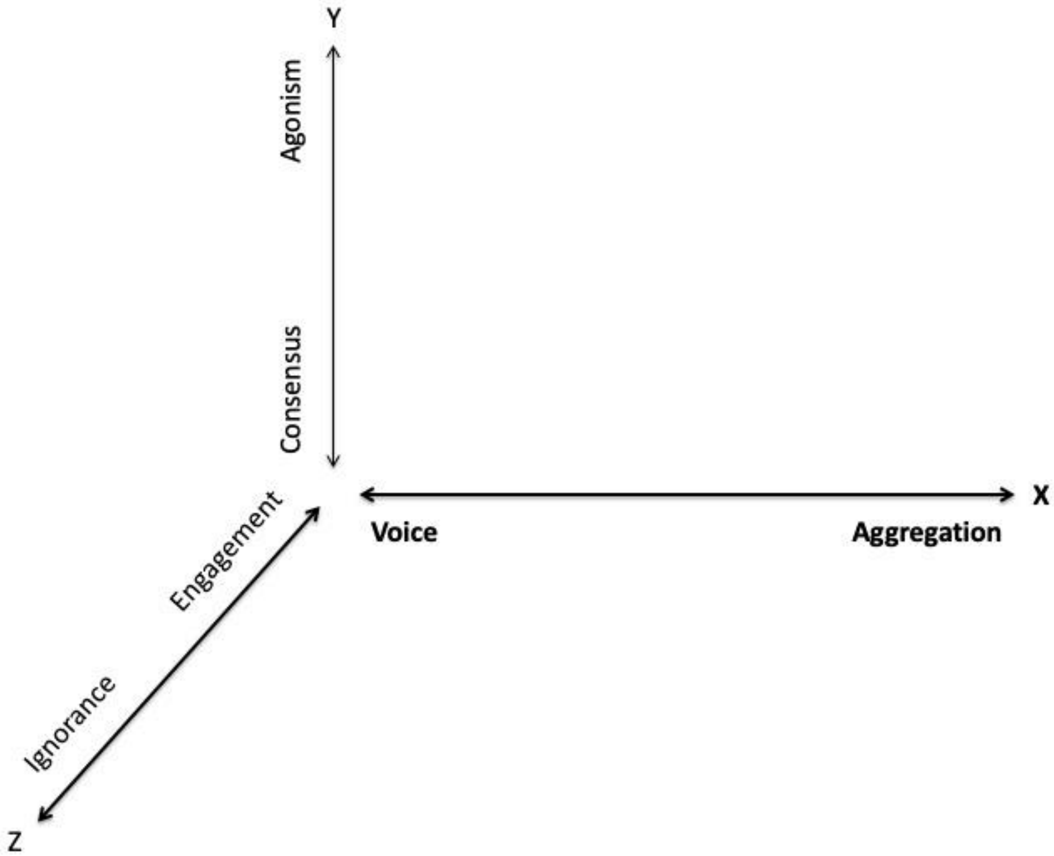

FIGURE 1.0 – THE TRIAXIAL MODEL.

Voice versus Aggregation

The main axis (X) puts public opinion on a continuum between aggregation and voice. Here, voice is tightly linked to the practice of deliberation. The term voice is used in order to signify the free and deliberate voicing of opinions, which is not necessarily part of a formal deliberation process. The axis is born from the premise that public opinion is construed differently when it is the result of an aggregation of predetermined preferences delivered privately and anonymously by individuals (Gallup, 1957, 23) compared to a setting where individuals first voice their opinions to each other and as a result of public interaction produce collective thoughts (Bohman, 2000, 195).

The idea behind the main axis is loosely adopted from the distinction proposed by Splichal (2012b) and reiterated in Gayo-Avello (2015) wherein normative-critical public opinion is contrasted with opinion polling. The former represents the ideal (Habermasian) deliberative constellation with the latter simply being the typical, non-interactive aggregation of opinion through survey statistics. In this thesis the concepts are expanded and put on a continuum so that public opinion comes into being containing either aggregative or deliberative characteristics, which roughly depends on the degree of complexity it can represent and the amount of interaction among agents it allows for.

Aggregation refers to public opinion as a product of tallying, quantifying and in some sense simplifying the form of public opinion. The most obvious example of aggregation is the process of voting, where the public opinion outcome is simply a matter of counting how many votes have been cast for each possible choice. The main identifying feature of aggregation is that it requires nothing of the individual other than stating a preference from a selection of predetermined options.

Deliberation in its purest form is the continued exchange of ideas and opinions until all participants consider the matter exhausted. From this iterative communication process public opinion is formulated. A critical note on the concept of deliberation; it is, in theory, often assumed to consist of a discourse that is rational and consensus-oriented (e.g. Habermas, 1984; Dryzek, 1990). In the triaxial model voice refers to the process of engaging in deliberation in any form however simple and does not assume that participants attempt to reach consensus or employ rational arguments. Thus, the main identifying feature of deliberation is that it requires interaction between individuals as the basis for public opinion formation.

It is important to understand that as part of having aggregation and voice be on opposite ends of a continuum, both terms must be applicable with a degree of fluidity. A useful way to elaborate what is meant by such fluidity is by invoking Zuckerman's (2014) concept of participatory civics that place *instrumentality* and *voice* on opposite sides of a continuum. Instrumentality is associated with activities that seek to capture public participation within technical procedures that clearly express the public's wishes, such as collecting signatures for a petition. Voice on the other hand is realized in activities that let individuals express themselves using their own words or actions, such as public hearings. In the triaxial model voice is viewed as interchangeable with voice and similarly aggregation as interchangeable with instrumentality.

At the very extreme of the aggregation end of the axis one might place the referendum where participants are allowed only the binary choice of for/against. One might then place a national election in a mixed-member proportional (MMP) electoral system just a little closer to voice and a standard opinion survey even closer. Opinion surveys do not contain any potential for actual deliberation, but since the aggregation procedure in that case accommodates a tiny bit more complexity (there are more choices) than a referendum, one would place them a closer to the middle. Voice at the extreme end of the axis cannot be illustrated with a clear institutionalized example from contemporary society. Rather it is an ideal pertaining to any decision-making process where no quantification of individual opinions is necessary, and the final outcome is a product of the consideration of every participants' views in all their particularity into a distinct notion. All people who are affected by the consequences of the opinion being established should have their voice added to the discussion. A parliamentary debate preceding a political settlement is, on the surface at least, a good example of a situation that would lie at the voice extreme on the axis. Concepts related to both extreme ends of the voice versus aggregation axis will be examined in greater detail later in this chapter. The utility of the triaxial model depends on both aggregation and voice being somewhat fluid terms. For example, deliberation pertains only to 'engaging in the process of deliberation' or simply using one's own modes of expression with no expectations about *how* it is carried out. A main argument of this thesis holds that this separation is increasingly necessary as a response to changing media technologies.

Consensus versus Agonism

The second axis (Y) places *consensus* and *agonism* on opposite ends. The idea behind this spectrum is directly derived from Chantal Mouffe's concept of *agonistic pluralism* (1999; 2000). Agonistic pluralism challenges earlier theorizations of the democratic function, especially those that have grown out of the Habermasian tradition of deliberative democracy. This is also why the term deliberation is often theoretically combined with an orientation towards consensus (Benhabib, 1996b, 69). As will become clear throughout the chapter there are good reasons for separating consensus from deliberation, such that deliberation, as described in the preceding paragraph, is more descriptive and refers broadly to voice, interaction and the continued exchange of ideas.

Many deliberative democracy theories hold that the democratic process combined with an ideal form of communication (fair and rational debate) would allow differences and disagreements within society to be smoothed out or transcended (Benhabib, 1996a, 77). Agonistic pluralism claims that relying on the prospect of such transcendence will obscure hidden power relations within society thereby putting the hegemonic order in a virtually unchallengeable position (Mouffe, 2000, 100). Hegemonic order inevitably constrains what can be considered a meaningful consensus. From the perspective of agonistic pluralism, democracy can never grow beyond the borders of the dominant hegemony as long as it insists on chasing an illusory idea of consensus. Instead the struggle over hegemony should be brought to the centre of the democratic process so that any provisional hegemony can always be openly challenged and subverted (Ibid., 102). It is this constant struggle over the implementation of ethico-political principles without assuming that a consensus must be reached that lies at the heart of the term agonism. A simpler view of the consensus-agonism continuum is to see it as a trade-off between agreement and inclusion (Linaa Jensen, 2014). The term consensus does not apply only to communication that has consensus as an outcome, but to all situations that are *oriented* towards consensus (Chang & Jacobson, 2010, 644). Thus, the main determinant of the axis is whether public opinion is oriented towards consensus or not.

This thesis does not assume any preference for either consensus or agonism. The main reason for including the axis is to emphasize that different publics can form politically relevant opinions that are geared both towards agonism and consensus.

Engagement versus (Rational) Ignorance

The last axis (Z) reports on the relation between engagement and ignorance. It is determined by the amount of time and energy that an individual will spend on gathering information and engaging in activities such as political discussions, local meetings, campaigning etc. Engagement versus ignorance is not only related to how much political knowledge people have, but also encapsulates how much engagement from the public should be expected in the first place. The premise of this axis can be traced back to the notion that the public is potentially fickle. Even opinion that is supported by an overwhelming majority of the public might not contain any truth (Hegel, 1821/1971, 203-204). Raw public opinion can potentially be a dangerous force as expressed by de Tocqueville in the notion of the tyranny of the majority (de Tocqueville, 2003/1840). This train of thought was further developed by Walther Lippmann in suggesting that the majority of the public has limited time and resources to engage in opinion forming activities, and thus public opinion should be guided by elites who possess the means to engage seriously (Lippmann, 1925/1998). On the flipside John Dewey, among others (e.g. Tönnies, Tarde), argues that public opinion functions best when all those who public opinion claims to represent are an active part in its creation and thereby making the main objective of democratic society to develop the structures and tools that would allow as many individuals as possible to participate in public opinion formation (Dewey, 1927).

This question about the engagement and fickleness of the public has in more modern times turned into what Aalberg & Curran denote as the 'rational ignorance debate' (2011, 9). The rational ignorance debate is contingent on a society that is saturated with information, much of it taking the form of entertainment or soft news (Bennett 2016). The quality of public opinion becomes a question of whether individuals can make sufficiently informed political choices without spending large amounts of time and resources seeking relevant information or engaging in civic activities (Kuklinski et al., 2001). Highly engaged people might outperform the less engaged, meaning they form opinions that more accurately reflect realistic expectations of cause and effect in society, but the less engaged might still do fairly well with much less effort (Sniderman, 2000).

Simply said, the relationship between engagement and soundness of opinion is likely to be non-linear. This kind of rational ignorance has been expressed in the idea of the 'monitorial citizen' (Schudson, 1998), which describes someone who is minimally watchful of public affairs but will spend most of her time pursuing personal goals. This follows from the larger scale logic that the 'soul of democracy' lies not with the public discourse of conversation and deliberation, but in the structures, processes and liberties ensured by democratic rule (Schudson, 1997). Still, it has been shown that without at least some level of critical engagement with media content, the public can be susceptible to mass manipulation (Jerit & Barabas, 2006), which places more emphasis on the need for fostering public engagement.

The role played by ignorance in public opinion, at least in the triaxial model, must be understood as *rational* ignorance. It means knowing or doing just enough to be a politically efficacious citizen in a representative democracy. Public opinion as a result of great engagement by the people it represents has a clear advantage in that it is likely to come from a well-informed place, however ignorance can be of great value as well because it demands less from people, which can lower the entry threshold for many people making it more likely for them to participate at all.

It is important for the purpose of this thesis that each axis in the triaxial model contains no implicit normative predispositions. Deliberative is not considered superior to aggregation and so on. Table 1.0 is a simplified illustration of the main problems and benefits pertaining to the endpoints of each axis. The following sections will attempt to place different conceptions of the public within the triaxial model. However, it is not relevant to meticulously go through each axis for every single concept. Some concepts are primarily characterized by their position on one of the axes while remaining flexible on the other two. It should be mentioned that the purpose of the triaxial model is not to quantify or create a grand theory of the public, but to help bring theoretical focus to the many disjoint conceptions of the public.

Endpoint	Pro	Con
Voice	Allows for complex negotiations where participants can potentially develop their viewpoints through a continued suggestion/response process.	Can be resource intensive, especially when trying to accommodate many participants, which might lead to exclusion of people and produce results that are difficult to summarize.
Aggregation	Can accommodate more participants with fewer resources and results are easy to summarize.	Opinions are pre-emptively funnelled into static categories with the risk of oversimplifying opinions and shut down the possibility of participants learning from each other.
Consensus	Agreeing on a single, combined viewpoint makes it easier to reach a concrete decision or response.	Being overly concerned with reaching consensus might create the need to shut down minority or 'irrelevant' voices thus excluding opinions.
Agonism	Can accommodate larger and broader ranges of opinions and does not exclude voices that do not agree with the majority.	Risks being less constructive sustaining shaky foundations for progressing and formulating collective decisions.
Engagement	Opinions are more likely to create a strong connection between expectation and reality when produced by informed and engaged participants.	Can be an unreasonable requirement for participants that do not have sufficient resources.
Ignorance	Participants can have their voices count without spending too many resources providing added freedom and satisfaction in personal affairs.	Can produce responses that lead to undesired results or the manipulation of participants by dominant figures.

TABLE 1.0 – PROS AND CONS OF EACH ENDPOINT IN THE TRIAXIAL MODEL.

Point of Departure: The Bourgeois Public Sphere and Related Concepts

The concept of the public sphere has become a cornerstone in media research related to democracy and politics. The use of the concept most often has its roots in the ideas envisioned by Jürgen Habermas (1962/1989). Habermas' concept of the public sphere has been subject to much critique and many adaptations but continues to be used as a foundation for theorizing how the public communicates with democratic rule (Lunt &

Livingstone, 2013).

Most media research adopts a version of the public sphere that is more loosely defined than what was originally conceived by Habermas. The original concept was built on the idea of a bourgeois public sphere, which refers both to an ideal as well as geographically and historically specific period. The ideal public sphere is traced through the political development in Great Britain from the turn of the 18th century to early 19th century. Within this period optimal conditions arose that allowed private people to come together in free deliberation over matters of common concern with the purpose of establishing a public opinion to serve as a guiding principle for the general rules and regulations enforced by the state (Habermas, 1962/1989, 27). One of the distinguishing features of the bourgeois public sphere is the division between *opinion* and *public opinion.* The division is derived from looking at the Rousseauian tradition, which emphasizes opinion characterized as simply the general spirit of the people with no element of critical deliberation and free of discursive power relations, in opposition to the British and German tradition, especially the Kantian, where the public use of reason (critical reason) is seen as the very element that constitutes public opinion and allows for the public to penetrate any manifestation of personal domination (Habermas, 1962/1989, 102; 121). Thus, public opinion should rely on the Kantian *public use of reason,* which constitutes the transfer of one's private concerns into a form that makes them relevant to everyone (the public) (Kant, 2013/1784). The social mechanism that helps ensure the occurrence of said transfer is sometimes expressed as "private vices, public benefits" meaning anyone who would privately wish to be excluded from the restrictions imposed by a certain law will under the condition of publicness wish to do the opposite, since all members of the public will have the same knowledge and suspicions toward each other (Habermas, 1962/1989, 179).

According to Habermas the societal changes imposed by the advance of mass communication technology, mass democracy and the welfare state, which made the public susceptible to manipulation and caused private trade relations to be intermingled with state control, led to the downfall of the bourgeois public sphere and caused an effective re-feudalization of society (Habermas, 1962/1989, 253). It is especially this scepticism towards structures, which many would consider unavoidable in modern, liberal democracies, which has served as a point of departure for much subsequent critique. The idea of the bourgeois public sphere has been criticized for being exclusive and anti-feminist, historically inaccurate and trapped in an unrealistic normative ideal (Fraser, 1990). However, it has been noted that Habermas has accepted much of the critique and expanded his overall view on the function of the public sphere (Lunt & Livingstone, 2013; Dahlgren, 2002).

Ideas pertaining to the deliberative function of the public were further developed in Habermas' later works. They can be seen as a more general formulation of the theory of the bourgeois public sphere that describes the norms for how public opinion is ideally formed. Deliberation should be carried out under the condition of publicness, signifying general visibility, unrestricted access and publicity, and discourse should be oriented towards reaching a mutual agreement (Habermas, 1990, 88-89). A set of criteria pertaining to comprehensibility, truth, appropriateness and sincerity (Habermas, 1979, 58-59) is necessary for instituting what Habermas denotes as *communicative action,* which guarantees that discourse is oriented towards consensus in opposition to *strategic action,* which is only oriented towards the interests of the acting party (Habermas, 1984, 333). A more simplified version of Habermas' ideal discourse is to say that it should be rational and reason-centred (Robert & Crossley, 2004), however it is important in this context that Habermas distinguishes between instrumental rationality and communicative rationality, with the former being entirely empirical and directed toward a predetermined goal and the latter being a product of unrestricted, argumentative speech and oriented towards consensus and mutual understanding (Habermas, 1984, 10). Thus, in the context of this thesis, it seems appropriate to place the bourgeois public sphere and the extended concept of communicative action in the metaphorical origin (0,0,0) in the triaxial model, meaning that it is characterized by a high degree of voice, consensus and engagement. To ensure theoretical clarity, when addressing the conflation of both the early and later works of Habermas the term 'Habermasian public sphere' will be used as distinct from the bourgeois public sphere.

The idea of the bourgeois public sphere serves very well as a point of departure to which all succeeding concepts of the public can be related. As will be shown in the following sections, many of the problems connected with the bourgeois public sphere lies with it being too close to the extremes on all three axes in the triaxial model.

Evolving Conceptions of the Public

In response to the aforementioned critique of Habermas' original concept of the public sphere as well as the expansion of mass democracy and development of new media technologies, scholars have sought new conceptions to better accommodate the dynamics of contemporary society. Discussions revolving around the concept of the public sphere since Habermas' early work was translated to English in 1989 can be divided into two main stages. The first stage concerns defending the virtues and benefits of increasingly pluralistic societies and the progression of its institutions (Interests groups, activists, investigative journalism etc.), while also pointing out the falsity of some of the historic accounts that have shaped the normative functions of the bourgeois public sphere (Dahlberg, 2011). The second stage is linked to changes in the media landscape loosely centred on the question of whether the internet has potential to revitalize the public sphere or be the cause of its ever-expanding fragmentation.

The initial critique of Habermas came as a natural response to the fact that he chose to exemplify his ideal public sphere using a historical period where 'the public' consisted only of a small elite of well-educated, property owning men. The function of the bourgeois public sphere is inadvertently conditioned on exclusion and repression of many parts of society (Eley, 1992, 321), especially women (Fraser, 1990). Aspects of mass democracy such as women's right to vote and proliferation of workers unions might compromise the basis for an ideal public sphere (bourgeois public sphere) as Habermas somewhat suggests in his early work, but most people today would still much prefer how things are organized today compared to 18^{th} century Britain. Some critics have claimed that the institutionalization of the public sphere itself during the early days of European democracy was made to silence unwanted, marginalized voices and create a sense of consensus where none really existed (e.g. Hetherington, 1997).

Extending the original feminist critique into a broader trend that has run counter to Habermasian notions of the public sphere is the idea that the personal is political (Papacharissi, 2010, 37). Critics have sought to challenge the discourse restrictions imposed by Habermas such as ideals pertaining to rationality and other deliberation norms (i.e. communicative action) (Plummer, 2003), which direct people toward disregarding issues that might be considered too personal and peculiar. Rather than leaving personal issues at the door in the pursuit of appropriate public deliberation, concerns pertaining to family life, gender, sexual preference, medical issues, cultural identity and the like are considered to have strong political relevance, which is sometimes referred to as 'identity politics' and linked to larger societal trends (Fraser & Honneth, 2003). In the same line, Habermasian theories have also had a tendency to promote only deliberation that is reason-centred and detached (Dahlgren, 2009, 83), almost echoing the Kantian norm of 'disinterested judgement'[5]. Deliberation that is fuelled mainly by passion about a cause, without striving to put one's thoughts into the most logically bounded and reasonable arguments possible, have often been considered a subverting mechanism potentially detrimental to democracy (Hall, 2013, 13). While not advocating the idea of passionate engagement completely devoid of reasonable argumentation, many later theories have considered at least the interconnection between passion and reason and how both are important ingredients in the development of citizens' democratic identity (Papacharissi, 2013; Dahlgren, 2009; Mouffe, 1999, 756). Emotionally based public opinion formation can, at the very least, be a powerful precursor to more formal deliberation processes (Wessler & Brüggemann, 2008, 5).

In addition to the reemphasis on the political relevance of opinions that are personal in nature and induced by passion rather than reason is a defence of the critical function of the press, which, in Habermas' original critique was considered to primarily administer manipulation and pacification of the public. Habermas' very negative view of the mass media has been accused of being too exaggerated (Hartley, 1996, 87), elitist (Dahlgren, 1995) and trapped in a hypodermic needle paradigm of media effects (Billig, 1991). In reality the press serves many functions that are just as potentially beneficial to the public as they can be detrimental. Just as those in power may attempt to use the media for manipulative and distractive purposes, the media also helps the citizenry by keeping them informed about general concerns and might act as a watchdog to keep governments and other powerful actors in check (Nerone, 2015, 143), which constitutes a classic view of the democratic function of the press. It is obvious that the concept of the public sphere presented by Habermas has been considered useful, especially regarding its main

[5] (Kant 1790, 5: 204–210 [2000: 90–96: 42–50])

function of facilitating deliberation between members of the public over matters of common concern. In order to reach a more inclusive concept, scholars have sought to simply transpose the public sphere onto the media; meaning contemporary media practices are considered able to support this main deliberative function, although in a very different manner than the bourgeois public sphere. This is sometimes referred to as the *mediated public sphere* (Brants & Voltmer, 2011; Couldry et al., 2007). Actions taken by decision makers are communicated to the public and societal issues that are important to the public are transferred back to the decision makers via the mass media thus instituting a deliberative function. As will be discussed in the following chapter, social media technologies offer the potential for the public to participate more directly in the process of discussing and sharing political information, rather than mass media simply being representative of the public.

In tracing evolving conceptions of the public further it is the changes in media technology that comes to the forefront. Habermas is criticized for delivering an account of mass media that is overly negative. However, other scholars have voiced concern about the dominant mass media technologies, TV, radio, newspapers as serving the construction of passive audiences (Herman, 2000), that might, in the long run, steer people away from public engagement, confining them in their homes and discouraging larger democratic community(ies) (Putnam, 2000). Furthermore, media organizations and journalistic practices are vulnerable to many implicit biases pertaining to elite interests, economic concerns and ideologies (Herman & Chomsky, 2010/1988).

The popularization of the internet has thrown a new, very significant piece into the discussion about media technologies, the public and democratic engagement. While not settling the discussion, there is no doubt that the internet and related technologies have disrupted the stable relations between sender and receiver typical of a mass media dominated world. In this thesis it is worth highlighting two[6] of the most often discussed consequences for conceptions of the public: 1) the possibility for the public to play a more active role in media production and consumption, and 2) the potential fragmentation of the public sphere.

[6] There are more important consequences, such as globalization and the expansion of global publics (e.g. Volkmer, 2014). However, they are less relevant or lie outside the scope of this thesis.

Givskov & Trenz (2014) describes the first consequence as a transition from attention publics to voice publics. It is important to note that people still watch television and read newspapers in the internet age, but the concepts are illustrative in highlighting a key difference, namely that many of the online digital platforms available with the internet have, at least nominally, increased the potential for each individual member of the public to have their voice heard. This potential for having a more active public, endowed with agency through technology, has been cause for some early proclamations that the internet can somehow revitalize the public sphere (Barber, 1998). However, it is almost common sense that just because you are able to voice your concerns does guarantee that anyone is listening. The possibility to engage with content and other people through online digital media platforms can come to constitute a kind of 'faux interactivity' bringing very little potential for actually influencing the political process (Koc-Michalska & Lilleker, 2017, 2).

The second main consequence of the internet has to do with an increased fragmentation of the public sphere (Bennett & Iyengar, 2008), a trend that had already begun with the proliferation of technologies such as cable TV and DAB radio. It is a consequence of the individual having more control over the selection and consumption of information. Publics can easily become more specialized focusing on common concerns that are only common among a very specific congregation of certain individuals, which creates new spheres of sub-politics (Papacharissi, 2010, 101). This trend can be seen as empowering (Dahlgren, 2005), as when previously scattered members of a group of minorities (e.g. diaspora) are brought together. But it can also be seen to make the individual's information environment more difficult to navigate (Papacharissi, 2002) and unintentionally instigating group polarization (Sunstein, 2002).

This fragmentation can also be attributed to the increase in media categories and modes of communication itself (Wells & Thorson, 2017, 35) making the age-old question in media research of 'Who says what to whom, through which channels with what effect?' decidedly more difficult to answer, which in turn makes publics and functions relating to the public sphere harder to identify. Additionally, another argument has been presented, which, at first glance, would appear to run counter to the fragmentation theory, namely that the internet has contributed to an increased centralization of the public sphere (Hindman, 2008). Indeed, the internet has been framed both as an amplifier (Keen, 2011) and silencer (Karppinen, 2009) of minority voices. It is not unlikely that fragmentation and centralization are occurring simultaneously. Some of the evidence for this has been offered by Helles (2013), which shows that internet activity is split between spaces that are extremely popular and central (i.e. Facebook, Wikipedia, international media sites) and those that are highly specialized and narrow (i.e. fan blogs, closed discussion forums, hyperlocal media sites). Thus, the online public space is becoming increasingly fragmented and centralized at the same time; it is the middle ground which is disappearing.

The implications that online digital media hold for the public as an opinion forming body will be unfolded in much greater detail in the next chapter. This section mainly served as an introduction to how and why different conceptions of the public have evolved since the popularization of the public sphere as a distinct concept. What follows is an account of some of the more specific concepts of the public that are relevant for the topic of this thesis.

Formal and Informal Publics

This part of the thesis will address the function of the public with respect to how public opinion formation happens on multiple levels, not least because this potential continues to grow with the expansion of media technologies.

The public is never a singular fixed point in society. Publics, collectives of people, continuously form in different ways and hold varying capabilities. One of the most persistent distinctions in both past and current representative democracies is that between *formal* and *informal* publics. It was conceived by Fraser (1990) in the early critique of Habermas' public sphere as strong and weak publics, but later adopted by Habermas (1996) under the labels formal and informal. According to Fraser the primary difference between the two is that formal publics have the power to make binding decisions on the issue being considered whereas informal publics can only form opinions. For the democratic society as a whole one would say that the parliamentary body is a formal public whereas the general citizenry is an informal public. This distinction is very sensible, almost common sense to anyone who have grown up in a democratic system where each Member of Parliament represents a fraction of the general public and is granted the time and power to take part in deliberation and decision-making on behalf of that part of the public. As mentioned previously, continually maintaining a connection between the formal and informal publics is often seen as being the primary political function of the Press. The broad workings of parliament, the Press and the general public mentioned are central to the tenets of representative democracy and an almost trivial thing to reiterate. However, it is vitally important to always have in mind the distinction between formal and informal publics as they carry with them different features and potential issues.

In relation to the triaxial model outlined in this thesis, a formal public will be located towards the engagement endpoint while informal publics will lean more towards ignorance, which is probably the most obvious difference. MPs simply have more time and resources. This is not to suggest that the general citizenry is completely unengaged. Some citizens are highly interested and highly engaged in the goings on of society, but in the mediated public sphere view of the mass media era people mainly engage as an audience with fewer possibilities to express themselves and come together as a public. With a few exceptions such as protest actions members of the general public only vote once every three or four years and do not engage in regular debate, while MPs have long sessions of discussions on a weekly basis. Albeit, it should be noted that MPs have some implicit restrictions, which can be traced back to Habermas' earliest theory of the public sphere that posits political parties in mass democracy as actors representing and advocating certain political positions (Habermas, 1962/1989, 165) meaning they are restricted to the use of instrumental rationality mentioned earlier. Another way of saying this is that political parties in mass democracies can only negotiate, not deliberate in the strict sense. It is not suggested that the general public engages in more deliberative practices than Members of Parliament, but it is an important quality that the general public are all in all more unrestricted in their communication. They are allowed to learn, change opinion and supposedly make up their minds as free, rational agents.

The distinction between formal and informal public is not analytically sensitive to the specificities of opinion formation, but it is important to highlight. Any conceptualization of public opinion that is not purely theoretical needs to address how information can flow from informal to formal publics. This thesis does not seek to provide an exact answer to that question, but it is especially important when evaluating the role of media to be constantly mindful of this distinction because the consequences for how opinion is formed in an informal public might differ depending on how the flow between the formal and informal publics is conditioned.

Polled Publics

The term 'polled public' is not commonly seen in the literature. It is invoked here to highlight how opinion polls and related techniques are ways of calling the public into being. As mentioned earlier, opinion polls are usually not considered to even constitute a public since there is very little publicity, however the inclusive framework proposed in this thesis makes it necessary to consider opinion polls as special instances of the public rather than not publics at all.

Polled publics come from opinion polling, which is most often tied to the developments of survey techniques by George Gallup in the 1930's United States (Gallup & Rae, 1940). A thoroughly technical approach, opinion polling had a big impact on the theoretical debate about public opinion since the techniques made it possible to accurately measure how an entire population thought or felt about a political decision, issue or actor. Political scientists or other experts devise a series of questions or statements that typically have fixed answers or responses relating to how enthusiastic the respondent feels about a political proposition. This technique has been considered especially appropriate since it directly mirrors the voting process and keep individuals free of the discursive influences of others since responding to surveys are done in private (Gallup, 1971, 227).

Driven by Gallup himself, the introduction of opinion polling saw the rise of advocates against earlier theoretical conceptions of public opinion in the face of new and effective measurement techniques. Why are long and chaotic debates needed when we can just ask people in a way that is representative and easy to summarize? Opinion polling has since received critique for being too static and constrained, meaning it does not inspire individuals to develop their opinions through an open intellectual process, in part because opinions have to fit within the response schematics of a particular, externally subsidized survey design (Ginsberg, 1989). The lack of individual voice and publicity makes opinion polling an aggregate of sentiments rather than a representation of people's actual opinions (Splichal, 2012). By not requiring opinion formation to be a public procedure the potential reliability and quality of its final expression is significantly decreased (Bohman, 2000).

The purpose of opinion polling is to elicit opinions that can be aggregated; thus, emphasis is put on aggregation over voice. It is not oriented towards consensus nor towards agonism; depending on the survey design and respondents, both things can come about (Stéphane, 2008). While requiring slightly more engagement than casting a single vote in an election, taking part in an opinion poll favours ignorance over engagement.

Mini-Publics

The concept of mini-publics can be seen as an attempt to create a hybrid between formal and informal publics. Some of the initial ideas are often credited to Robert Dahl (1989), but as mentioned by Goodin & Dryzek (2006), the popularization of the concept followed the "deliberative turn" of democracy studies in the 1990s (e.g. Fishkin, 1991; Benhabib, 1996; Bohman, 2000). The deliberative democracy movement puts great emphasis on the practice of real deliberation, especially between lay people, or those of the general public. One of the most typical concrete manifestations of a mini-public is the so-called "deliberative poll" (Fishkin, 1991), where lay people are selected and put together with the directive to deliberate on a specific topic. The hope is that by formalizing a setting for regular people to participate in deliberation and address important political issues, a mini-public can serve as an improved vehicle of opinion in opposition to the mass attention publics of the voters/media consumers (Dryzek, 2006, 3). It is important to note that even the formal creation of a mini-public such as a deliberative poll still retains more similarity with an informal public as it is not meant to have legislative power, except in rare cases (Ferejohn, 2005), but rather complement parliamentary decision-making (Budge, 1997, 7).

Although the deliberative democracy movement is unique, it can still be seen as having strong ties to the Habermasian tradition of rational debate and consensus-oriented discourse as was mentioned previously in this chapter. Mini-publics can take many concrete forms, even some that explicitly seek to not pressure participants towards consensus (Fishkin, 2005). The ideal is still to transcend differences of opinion rather than just clashing them together. Not surprisingly the concept of the mini-public can be placed fairly close to the ideal Habermasian public sphere at the metaphorical (0,0,0) coordinate in Fig 2.0. It has deliberation at the very heart and thus might not be easily summarized (aggregated) unless measures are taken to restrict what parts will be counted as part of the final output of the public deliberation, a deed, which in deliberative polls is often carried out by an impartial moderator or through voting at the end (Landwehr, 2014). Depending on the setup a formal mini-public might require a fair amount of engagement, which can discourage people with low resources from participating; a problem that has been duly noted (Jacquet, 2017).

This chapter has outlined some of the major distinctions between publics and non-publics and presented the triaxial model as a framework to describe different perspectives on public opinion and the interrelations between them. The public sphere tradition has been introduced, starting with Habermas and onto some of the main ideas regarding the function of public opinion through critiques of Habermas and changing media landscapes.

The following chapter will take a more contemporary look at public opinion, specifically in relation to online digital media and social media. First by describing some of the main characteristics of online digital media and then examining them in relation to more recent theories of the function of the public with respect to the triaxial model.

Chapter 2. New Media, New Publics

Online Digital Media and Social Media

At the time of writing social media and online platforms in general are considered an integral part of life, even for the minority of people who do not use them. Popular online venues such as Google, Facebook, Twitter, Wikipedia etc. have been around for almost 20 years. Calling such platforms 'new' can seem a bit strange, however online digital media, along with the devices on which they are accessed (smartphones, laptops, tablets), can still be considered the latest, game-changing macro-level category of media. The fact that online digital media have changed so much for how the public engages with politics has necessitated the development of entirely new conceptions of the public. Some of the general trends in public sphere theory that were already identified in the early days of the internet were briefly introduced in the previous chapter. This chapter goes into detail about the intricacies of online digital media that are necessary to understand newer conceptions of the public. The present section will consider three main trends pertaining to online digital media: 1) media convergence and hybridization, 2) user-generated content and user interaction, 3) mediatization and personalization.

The digitized environment known as the computer, whether it is a phone or laptop, is considered to be the physical, outer frame of not just social media, but all online digital media. Computers have their own materiality, typically a screen, speakers and a tactile interface, however they are effectively *meta-media*. It means they pull together all sorts of content that was previously considered to be intimately linked to its own physical medium, thus negating McLuhan's original one-liner[7] into 'the medium *was* the message' (Jensen, 2010, 84). The features and manifestations of meta-media have been a popular topic in media theory such as Bolter & Grusin's (2000) concept of *remediation*, Jenkins' (2006) *convergence cultures* and, the most popular notion in recent literature, online digital media as *hybrid media systems* (Chadwick, 2013). However, they all share the same

[7] Marshall McLuhan's famous quote: 'the medium is the message' (1962).

basic notion, namely that the digital computer creates a space for media convergence where traditional media are available side by side with new digital media forms. Not only do they appear simultaneously, but content that has a certain form when distributed through one channel might be creatively appropriated by members of the audience and re-communicated in another place (Jenkins, Ford & Green, 2018). An example could be when a digital television broadcast is edited so that the same 20 seconds loop continuously to create a satiric effect, and then shared on social media. Since content can be endlessly remixed and shared with effect, the message that one receives depends very much on one's place in the communication network. A clear consequence of hybrid media systems is the increased difficulty of locating media effects as categories are becoming so intermingled that it is no longer realistic to ask people about exposure to specific types of media (Wells & Thorson, 2017, 35). From the perspective of media production this can be referred to as narrowcasting in opposition to broadcasting (Scheufele & Nisbet, 2013) or as a transition from a 'push' to a 'pull' model of communication (Webster, 2011). In a hybrid media system content can no longer simply be pushed through established channels, it has to be 'on-demand' and available to the user on their terms. A typical strategy for accommodating such changes is to give media content a cross-platform presence, making it available for consumption and/or engagement in multiple settings (Ksiazek, Peer & Lessard, 2016). Hasebrink (2016) argues that the view of 'shared news consumption within a nation state hooked to the mass media' has been surpassed by the individualized practices of social media. For the same reason there is a call for a re-emphasis on the uses and gratifications lens, focusing on how people use media technologies and not what technologies do to people (Shah, McLeod, Rojas, Cho, Wagner, Friedland, 2017, 492).

It can be difficult to separate traditional media from those that can be considered truly novel. And even more since analogue, offline media are still widely used as well (Helles, Ørmen, Radil & Jensen, 2015). A useful distinction is that between *digitized* and *natively digital* (Rogers, 2013). Streaming TV and radio on a website would be a good example of digitized media forms in the sense that they are very similar to their analogue counterpart, though they are of course still subject to potential remixing; whereas the use of hashtags on Twitter does not have an obvious analogue predecessor. Phenomena that can be considered natively digital are also some of the main reasons for the necessity of theorizing new conceptions of the public, which will be introduced later in this chapter. Details pertaining to materials and historical definitions of what can be considered new and traditional media are outside the scope of this thesis, instead focus will be on the distinct consequence that hybrid media systems have for political communication.

The potential for creating, publishing and sharing user-generated content is considered one of the main advantages of online digital media. It is non-passive, brings a world of possibilities at a very low-cost of entry for regular people and fosters empowerment (Shirky, 2011). The arrangement supported by online digital media where people can be both receivers and creators of content has spurred the invention of terms such as produser or prosumer (Bruns, 2007). Combined with hybrid media systems, user-generated content has caused additional decentralization of media production and consumption mostly because of its capacity to be extremely specialized and appeal to never-before-conceived niche audiences (Gruszczynski & Wagner, 2016, Lee & Tandoc, 2017). Individuals establishing their own platforms have triggered a surge in alternative media content, which has even caused the lines between mainstream and alternative to become blurred (Stroud, 2011). Examples of this are when established journalists act as independent bloggers or private people become powerful 'influencers'[8]. A noted consequence is the rise of citizen journalism (Anderson, 2013), which is when private citizens, especially in situations where they are directly embedded in the context of the story, act as reporters using personal webpages and blogs. Another is the existence of a *viewertariat* (Loader & Mercea, 2011, 768), which constitutes a small percent of users typically on social media who are significantly more active than other users and act as the main opinion leaders both in terms of distributing and framing the content. There is much empiric evidence to support the active presence of such a viewertariat on the big social media platforms (Bruns, 2013; Bruns & Stieglitz, 2014)

In the same vein as user-generated content, online digital media also allow for user interaction. A popular strand of research has analysed the architectures and affordances found on online digital media platforms (e.g. boyd, 2010; Bruns & Moe, 2014 – see Hafezieh & Eshragian, 2017 for a review). However, the focus of this thesis is public

[8] The term influencer denotes an individual who has gained a significant level of fame exclusively through social activities. Influencers are then often approached and contracted by commercial enterprises for advertising purposes.

opinion and not media platforms and thus will only consider the general and most relevant characteristics. Notably online digital media have increased the reconfigurations of different degrees of communication such as one-to-one, one-to-many and many-to-many (Jensen, 2009). People can act as broadcasters on blogs and social media (one-to-many), have intimate conversations through instant messaging apps (one-to-one) and engage in comment threads and discussion forums (many-to-many). The different degrees can even be conflated, as when a comment intended for a single individual in a semi-public setting (e.g. Facebook's wall) becomes a trigger for multiple other individuals to join in. Just like how messages can be constantly remixed they are also subject to interpersonal and group-specific dynamics in terms of sharing and discussion. In essence this is not something new. Before the internet people would also share news via word-of-mouth, by saving a newspaper clipping or recording a tv-program, however this level of communication has been considerably intensified. With online digital media information consumption, sharing and discussion happen concurrently (Rojas, Shah & Friedland, 2011). One of the most extreme cases of this intensification can be found with the phenomenon of *dual-screening*[9] (Vaccari, Chadwick, & O'Loughlin, 2015), where individuals are watching a tv-program while simultaneously blogging about it on their laptop or smartphone. In the Lazarsfeldian tradition it can be considered a change from two-step flows to multi-step flows of communication (Jensen, 2016). Though it is worth noting that even with the heightened communication intensity, most online digital media formats are inherently asynchronous forms of communication, which some consider a positive feature as it allows time for individuals to reflect before responding to an issue (Androutsopolous & Staehr, 2018). In sum, increased interconnection and reciprocity should be considered some of the main characteristics of online digital media technologies.

Two often mentioned features of contemporary media environment, at the time of writing, are mediatization and personalization. It is interesting to note how both terms describe two sides of the same process. Mediatization denotes the way that media technologies are increasingly present in our lives and thus impose new media logics that influence our behaviour; everything from grocery shopping to charity work has a potential mediated dimension. Personalization then describes how media technologies

[9] Sometimes called second-screening.

make consumption and communication highly customizable; providing increased amount of choices about how to transmit, receive and engage with information. This two-sided process also highlights an often-reiterated notion, namely that affordances and communication practices pertaining to online digital media are created in the interplay between people and technology (e.g. boyd & Crawford, 2012; Lomborg 2011; Tierney, 2013). This stance is taken in order to avoid technological determinism, which has always been a tempting avenue for media research (Lum, 2014). Also, personalization is most often used as a general concept while mediatization has a much more distinctive theoretical foundation (Hjarvard, 2008). This section will not treat them separately as they both emphasize many of the same consequences of online digital media.

The trend of personalization is typically derived from domestication theory, where media technologies increasingly become an extension of the self, depending on how much they are integrated into everyday life (Haddon, 2011), which has become the case with smartphones, tablets and laptops this last decade (Helles, 2013b). The consequence of this is a more individual centred conduct and more flexible social relations (Rasmussen, 2014, 63-64). The individual user has more control over what, when and where they communicate with certain actors, however, as will be discussed later, the networked nature of online spaces also imposes some limits to how much absolute control the user has. From the perspective of mediatization, these new features of customization not only condition the communicative potential of the individual (Hjarvard, 2019), but also allow for the creation of entirely new kinds of sociality (Van Dijk, 2013). Last but not least, personalized digital media and increased mediatization produces new relationships between the individual and the self. The same way that a personal diary or notebook can be a way to interpret and interact with oneself, so does the increased mediatization, especially asynchronous, written forms, insert a reflective distance into much of one's everyday communication thus putting more emphasis on daily life as a performance (Rasmussen, 2014).

Central to all aspects of online digital media is the many ways they allow users to influence the creation and sharing of content, especially when compared to traditional mass media. The increased role that individual users, and networks of users, play in combination with the affordances offered by specific social media platforms, has a significant impact on how public opinion is formed. The next section will go into detail about how communication practices on social media affect flows of information.

Locating Media Effects: Curation and Expression

This section goes into further detail about how online digital media, especially social media, have affected the flow of information in society. As mentioned old and new media forms converge on digital platforms and communicative practices are constantly negotiated in the interplay between technology and people in interconnected networks, thus understanding who, how and to where information is disseminated key in order to approach the political consequences of citizen's complex media environment and participatory behaviour (Brundidge, Garrett, Rojas, & Gil de Zuniga, 2014; Valenzuela, 2013).

In an attempt to frame the complexity of information flows online, Thorson & Wells (2016) presents the concept of *curated flows*, which argues that media effects follow how any given individual is embedded within networks of content flows curated by different sets of actors. A weakness of the framework is that emphasis is put entirely on the distribution of information and pays little attention to the creation of content and the role played by creative professionals (i.e. media organizations). Using media resources as the main point of departure for subsequent conversation has long been, and still is, very common (Edgerly, Kjerstin, Bighash & Hannah, 2016; Della Carpini & Williams, 1994), thus details pertaining to how original content is shaped is important. Still it is useful to consider curated flows as the primary factor for contemporary media effects. For example, earlier media effects concepts such as agenda setting and framing are just as relevant today; the difference is that agendas are not being determined mainly by news producers, but by the whole network of information flows (Neumann et al., 2014).

For social media five typical kinds of curation can be identified: personal, social, strategic, journalistic and algorithmic (Thorson & Wells, 2016). Personal curation involves choices made by the individual about which information channels are selected and what content time is spent with. As mentioned earlier, many theories stress the increased ability to self-select content using online digital media, however in a social media context it is worth noting that this ability is greater in terms of choosing which actors to connect (Bode, 2012), whereafter the control over what content one is exposed to becomes limited. Choosing to follow certain actors on social media platforms determines which pieces of information show up in an individual's news feed (Gonzales-Bailon, Borge-Holthoefer & Moreno, 2013).

Social curation then is the filtering mechanism causing information selection to be greatly biased towards what is shared within an individual's social network. It should be considered a curation logic in its own right as it can have pronounced consequences since most people's primary reason for being on social media is pursuit of social goals (Lomborg, 2011, 56), which then unintentionally ends up determining the kinds of political input the individual receives (Graham, Jackson, Wright, 2016). Still, the effects of using social media can be particularly difficult to determine because personal and social curation logics can vary greatly between individuals. As an example, it has been shown that the link between using social media and greater engagement with politics is highly dependent on users' goals and expectations when connecting to the platform (Ekstrom & Ostman, 2015).

Strategic and journalistic curation respectively describe the roles of elite actors such as politicians on one side and interest groups and journalists and media organizations on the other in contributing to the information flow. Both are governed by more clearly defined objectives than personal and social curation in that they seek to amplify their message, get supporters, retain audiences and promote their position. They benefit from an institutional legitimacy and other elite endorsements that give them a more privileged position than ordinary people (Poell, Abdulla, Rieder, Woltering, & Zack, 2015), however at the same time the communication hierarchy is significantly flattened compared to traditional mass media (Khan, Gilani & Nawaz, 2012). In the news industry this is referred to as a change from gatekeeping, where journalists and editors have power over what gets published, to gatewatching, which signifies the important role of private people as intermediary distributors in their personal network (Bruns, 2005). For politicians there is a disruption in how they communicate with the public since social media lets them reach out to the masses directly thus circumventing the traditional channels they used to rely on (Broersma & Graham, 2015). Since social media are fundamentally interactive, the public has the ability to respond and voice their concerns to politicians and government agents, which has mostly been seen as a positive thing (Bertot et al., 2012), though there is also scepticism about how much influence such interaction actually provides (Tarta, 2014). Additionally, this has initiated a transfer from a mass media logic to a network logic in terms of how politicians seek to reach the public, meaning they are seeking to create messages that can spread well in social networks (Klinger & Svensson, 2015). This is an example of how strategic and social curation become interlocked, notably since the social level of networked communication has been identified as the most significant for messages to go viral (Ibid., 1249). This view also ties in with the argument of media convergence where the media is not as an intermediary between political actors and the public. Individuals, political elites and media organizations are all seen as actors in hybrid discursive flows (Chadwick, 2017). Eldridge & Bødker (2018) describes journalists as interlocutors rather than intermediaries. Journalists are both reacting to socially and personally curated information as well as redistributing, appropriating and soliciting content directly from social media (Harder & Paulussen, 2016). Such tendencies have been shown to be especially pronounced during breaking news events where the whole news media industry gets on the bandwagon, reporting information sourced uncritically from social media, which can later turn out to be completely unsupported (Bandopadhyaya & Kristensen, 2019).

Lastly there is algorithmic curation, which is determined by the technological infrastructure behind social media platforms. Social media act neither as creators, senders or receivers of information, or even as distributors in the traditional sense, but as digital intermediaries (Thorson & Wells, 2016, 317). Most of the popular social media platforms at the moment, Facebook, YouTube, Twitter, Instagram, have some kind of content feed that helps people find and select content within what can only be described as information saturated networks. The feed automatically makes suggestions and is thus governed by an algorithm that determines what content is shown to an individual. Such algorithms typically rely on metrics pertaining to the overall popularity of the content and individual users' previous engagement with types of content and specific actors (Nikolov, Lalmas, Flammini & Menczer, 2019). One key thing to keep in mind is that where social media very notably make sharing and interaction more visible and more public than before the internet, the processes behind the algorithmic curation remains largely invisible to most users (Jones, 2015). Some of the political consequences that can be attributed to algorithmic curation will be unfolded in greater detail in the next chapter.

As mentioned earlier, the introduction of social media can be thought of as a transition from attention publics to voice publics to which can be attributed the potential for people to express themselves. Thus, *expression effects* are often accentuated as a major factor for understanding contemporary media effects (Valkenburg, 2017; Cho et al., 2018; Shah, 2016). Some even claim that social media have made expression just as important as reception (Yoo & Gil de Zuniga, 2019, 1). Expression is significant for obvious reasons such as being the fundamental building block of conversation thereby supporting the organic distillation of ideas throughout society (Shah, 2007). However, since one of the distinguishing traits of social media is many-to-many forms of communication such as comment threads and posting forums, which encourages quick exchanges rather than lengthy conversation, scholars have turned their attention to how expressions affect not just the receivers, but also the sender of information (Pingree, 2007). In some sense, this idea is not new; Dewey (1938) pointed out how learning through expressive acts was many times more effective than the passive reception of dogma. It is mentally a more effortful and elaborate action and encourages one to relate to the self in anticipation of how others will respond to one's expression (Eveland, 2002). Accordingly, expression effects have been linked to increased political efficacy (Cho et al., 2009) as well as increased initiative for political action (Gil de Zuniga et al., 2014). It is important to keep in mind that expression is not limited to creating original content and writing comments but can also be done through the creative appropriation of other people's content such as pasting videos together or generating image-based memes (Jenkins, Ford & Green, 2018, 2).

According to Shah, McLeod, Rojas, Cho, Wagner & Friedland (2017) an emphasis on the level of interpersonal communication in the flow of information between all parts of the public should be considered the most significant aspect for locating contemporary media effects. The political consequences should therefore be analysed from the perspective of how people organize, manage and perceive their online information networks. In a similar vein, Cacciatore, Scheufele & Iyengar (2016) claim we have entered a fifth paradigm[10] of media effects centred on *preference-based effects models*. In line with the

[10] Kuhnsian oscilation between strong and weak effects models. McQuail.

general trend of personalization of media technologies, engagement with information revolves increasingly around our political preferences. According to the authors these preferences are most pronounced with social and personal curation, but also part of strategic and journalistic curation, and, although they do not mention it, algorithmic curation can likely be considered part of it too. Preference-based models alternate between weak and strong media effects, which are contained, respectively, in the concepts of *preference-based reinforcement* and *tailored persuasion* (Ibid., 19). The first is considered a weak effect because messages that are more or less in tune with preferences already held by the individual might only cause a slight reinforcement of attitudes without changing much. The second effect, however, considers those messages that are so adequately timed and personalized that they can persuade uncertain individuals to swing down a new path such as what the marketing firm Cambridge Analytica claimed to have done during the 2016 US presidential election (Grassegger & Krogerus, 2017), or cause people to advance their political preference towards a new grade of extremism (Hendricks & Hansen, 2016).

This section has presented a framework that highlights the primary forces affecting the flow of information through networks on social media platforms. To effectively explain this framework, the section has taken the perspective of the individual and their place in the interconnected network of strategic, journalistic, personal, social and algorithmic curation practices. The next section will discuss how such networks of information flow relate to public opinion as *collective* opinion and not just individuals in arbitrary networks.

Connectedness and Togetherness

There are many modes of being together with other people, which involve varying degrees of connection. It is common to conceive oneself to be closely connected to one's immediate family and long-time friends. The strength of connection then begins to weaken as we expand to extended family, co-workers and casual friends, local communities, nations and lastly humanity as a whole. Once we reach a certain level, our sense of togetherness can only be expressed as an imagined community since only a handful of people in the community will personally know one another, such as in a nation (Anderson, 1983). Being together also relates to space. Assembling in a physical space is the most natural expression, however any act of communication allows us to connect with other people. This is where media technologies offer an extended communicative space wherein connections can be established and maintained without any physical interaction (Newscomb & Hirsch, 1983). Connections are not necessarily products of a practical, economic need to exchange information. Habermas (1962/1989) noted how the reading and subsequent discussion of works of fiction lay the foundations for understanding oneself as part of a larger populace vis-à-vis the shared human experience. A useful lens for understanding togetherness and connectedness in isolation is the popular, but sometimes overlooked, notion of communication as both transmission and ritual (Carey, 1975/2002). Most studies of political communication and media technologies have focused on communication as transmission such as agenda setting, framing, priming, public relations, propaganda, where media are considered instruments of effects that can instil ideas and persuade people. However, communication, as the word itself would have it, is also the condition of community and a "…process whereby reality is produced, maintained and repaired" (Ibid., 23). Thus, independently of the content of communication, it is possible to conceive a parallel process of socialization, gluing people together and producing an overall sense of connectedness and togetherness, though it will of course always be related to the content.

Media technologies might technically connect people, but different kinds of media afford different kinds of connections. Around the turn of the millennium Putnam (2000) expressed concern that our ability to come together in local communities was in decline due to the dominance of mass media. The underlying argument is that mass mediated communication, which, when compared to face-to-face communication, is based only on passive reception of information, produces a sense of togetherness that is too abstract to sustain the public communities that have a collective agency of their own. The same concerns have been reiterated with the internet where an even broader range of communicative experiences is accessible from the physically isolated space of one's own home (Turkle, 2011). However, since online digital media provide many modes of communication that are in fact not passive, some have attributed such concerns to a bias against virtual (non-physical) togetherness (e.g. Rasmussen, 2014). Papacharissi (2010,

142) notes that the digital public consists of individuals that are physically alone in their private spheres, but not isolated.

What is central to the discussion about connectedness and togetherness comes back to the earlier introduced distinction between digitized and natively digital. Private instant messaging apps might simply produce a sense of togetherness that is similar to that of a phone conversation, mail correspondence or a face-to-face talk thereby being a case of digitized communication. Digitized communication in this sense is of course also being studied, however the greater challenge lies in conceptualizing the kind of connectedness and togetherness produced by natively digital media uses such as comment threads, retweeting networks and hashtag uses. Some would argue that the reason for a general decline in traditional modes of political participation lies with the transposition of political engagement onto these natively digital forms of communication (Hay, 2007; Ekmann & Amna, 2012). A term like 'community', which is normally used to describe collectives that form a strong bond through continued interaction compared to the random crowds of people that participate around trending hashtags on Twitter (Albrechtlund, 2010), is still relevant, and even useful in the light of digital tools. Facebook groups for example can be effectively used to maintain communities of cultural minorities who would normally have a difficult time finding each other (Marino, 2015). However, using only terms that are tied to offline phenomena is problematic and not sufficient for understanding the novelty of connectivity on social media (Mejias, 2010; Yuan, 2013). One of the simplest concepts of a meaningful political collective builds on the formulation of a symbolic 'we' in opposition to 'them', identifying an in-group and an out-group. There is a rich theoretical tradition that has explored this dichotomy (e.g. Schmitt, 1932/2004; Gamson, 1992; Mouffe, 2000), which lies outside the scope of this thesis. However, the transformation from a mass of opinions into a distilled, collectivized form of public opinion that has uniform power is akin to that of a group of people becoming a 'we'. The voice versus aggregation part in the triaxial model explains this collectivization of opinion as a fluid process, and as such people do not necessarily need to form a sense of belonging to a certain political group or collective but can form public opinion through more external means such as opinion polling. The last part of this section discusses the significance of coming together on social media through means that, on the surface, appear arbitrary and ephemeral.

The conceptualization of connectedness and togetherness on social media has come to naturally revolve around how socially significant these so-called natively digital forms of connectedness really are when compared to traditional forms. This is also tied to questions about the actual political power offered by digitally networked technologies. They may enhance our ability to solve everyday problems like finding a lost phone or selling second-hand goods, but are they really capable of enhancing our ability to challenge political, governmental and cultural hegemonies? (Bakardjieva, 2015, 986). One of the focal points of the debate locates *collective identity* (Melucci, 1989; 1995; 1996) in opposition to *connective action* (Bennett & Segerberg, 2012; 2013), which are both considering the degree to which formal organizations, individual agency and technology are necessary for people to collectively support a political cause. Both emphasize the important role that formal organizations can play, but do not see them as the sole driver of collective action. Instead, on a very basic level, Melucci's collective identity emphasizes the importance of individual agency that is employed in interactive processes of negotiation, interpretation and reflection in order to produce and formulate collective goals (Melucci, 1995, 43). The logic of connective action on the other hand postulates that many of the laborious cognitive tasks that are required for maintaining collective agency and organizing collective action have been replaced by digital tools that functions as organizing agents in their own right (Bennett & Segerberg, 2012, 755), thus emphasizing the role of technology. Tied to the concept of connective action is also the idea that the symbolic 'we' in opposition to 'them' can attain more fluid formulations. Bennett & Segerberg (2013) calls this *personal action frames*, where a political cause can be supported through meaning making that is mostly personal and somewhat disjoint. One of the most famous examples is from the political movement 'we are the 99%', which was organized around people posting their personal stories and sharing them on social media, but still under the collective banner of 'the 99%'. Seeking a conclusion to the debate is outside the scope of this thesis, however it will be assumed that digital online media are themselves powerful agents of organizations and that connective action can occur, but it must also be considered a delicate potential that might require the support of purposeful individuals or formal organizations in order to avoid having only a fleeting effect on people, which is what is often expressed as *clicktivism* or *slacktivism* (Morozov, 2012).

The greatest focus of this thesis is on social media communication in public settings (e.g.

commenting on public news posts on Facebook), which can easily be deemed the most short-lived and randomly directed acts of communication. Attempting to theorize connectedness and togetherness in these instances has largely been ignored in the research literature. One of the most relevant concepts is that of *momentary connectedness,* which describes "…computer--mediated publicness that allows polymorphism across layers of communication" (Rathyanke & Suthers, 2018, 10). Essentially feelings of connectedness are in most cases very temporary and are unlikely to have lasting effects, but at the same time they are also very malleable and inclusive and can be a cheap source of obtaining quasi-continuous forms of togetherness at a distance (Licoppe & Smoreda, 2005). The reason for people to be willing to engage and find such momentary connectedness meaningful is tied to the previously mentioned expression effects. Interactions are sometimes non-transactive and motivated by expression and experiences of connectedness rather than the exchange of opinions (Rathyanke & Suthers, 2018, 6). This is also an attestation to the polymorphic nature of momentary connectedness, that can develop in the direction of being either a *community of debate*, meaning it prompts further inquiry and engagement with an issue as well as potential deliberation, or a *dialogue of the deaf*, where people simply voice their opinion without seeking continuation or further learning (Ruiz et al., 2011).

Expanding the frame for what counts as collective opinion via concepts such a connective action and momentary connectedness risks puling public opinion so far away from any substantive political process that it hardly retains political relevance. On the other hand, they tap directly into the publics unrestrained opinion formation activities. Building on more recent concepts of the public, such as data publics, which will be presented later in this chapter, it will be considered How Big Data and the methods for measuring public opinion developed in this project can help to bridge this gap ever so slightly.

Counter Publics and Issue Publics

Counter publics and issue publics are not related in any obvious sense, but they are included in the same section here because they share a single key trait; both being concepts that address a concrete manifestation of public opinion in direct response to something else.

The use of counter publics as a concept, again, has roots back to the early critique of Habermas' bourgeois public sphere. Historically it points to the existence of groups of people who shared common ground on a range of issues but were most often not officially recognized (e.g. elitist women, laborers etc. in the early days of European democracy) (Fraser, 1990, 67). On a macro-level, the idea of a counter public can best be described as an organization of people that "…differ markedly in one way or another from the premises that allow the dominant culture to understand itself as a public…" (Warner, 2002, 81). In more recent media research the term is also applied at the micro-level, such as in cases where either a small or large group of people immediately rise up to challenge to premise of the information that they are presented with, which is something that social media and blogs have made much more prolific in the last decade by allowing publication of user-generated material and interaction with content in general. Thus, talking back, commenting on a piece of news online, can sometimes constitute a kind of counter public (Brooker et al., 2015, Toepfl & Piwoni, 2015). By presenting more niche perspectives commenting can significantly diversify the points of views that are attached to a story (Saez-Trumper, Castillo, Lalmas, 2013), and in some cases the general persuasiveness of a news article can be damaged by user comments (Winter, 2013). The key characteristic for counter publics is that they come into existence by resisting the very premise that the construction of another public is based on. On the macro-level this premise can be fundamental ethico-political concerns, and on the micro-level some basic, context-specific assumptions (e.g. poor people are lazy). In regard to the triaxial model counter publics are notably characterized by a very high degree of agonism. Also, they are more often considered in a form where public opinion does not rely on the distillation of many complex idea into a singular form. Instead simply being in opposition to a dominant viewpoint irrespective of concrete reasons can be regarded as relevant participation in a counter public, thus less engagement is demanded. And with social media technologies counter publics become even more easily aggregable. Massive disliking of a politician's post on Facebook is more easily quantifiable than the result of a multisided discussion yielding several perspectives.

The term issue public has, especially in media research, been used in many contexts, not always building on previous literature, which makes it one of the fuzzier terms to come across. Broadly, it points to the coming together of people in response to a specific current issue. Originally envisaged as a group of people who were particularly well informed and often personally invested in an issue (Converse, 1964/2006; Iyengar, 1990; Krosnick, 1990). Later works have highlighted that members of an issue public are not necessarily technical specialists, but 'specialists of passion' based on shared values, interests and identities directed toward a certain issue (Kim, 2009, 255), which seems to be in line with the progression of public sphere theory towards more discursively inclusive conceptions. It is important to mention that any kind of constellation of the public will consist of a group of people with something in common, and thus what is distinctive for an issue public is its very narrow expression (Poor, 2005). It is a very narrowly focused public. As mentioned in the beginning publics are plural, and any one person can be a member of multiple publics, but at the time of its construction an issue public is determined by its narrow motivation. This also makes an issue public pertaining to a certain case easier to identify, as it exists at a specific point in time (Brenes Peralta, Wojcieszak, Lelkes, & de Vreese, 2017), even though its members still possess fluid positions within the larger network of publics. It has been noted that on social media issue publics might sometimes be more appropriately termed ad-hoc publics (Bruns & Moe, 2014). This highlights the more arbitrary and loosely organized way that people can come together as a public on social media, especially compared to the traditional conception of issue public that would consider people to be heavily invested in the issue. Ad-hoc publics can be formed by people who do not necessarily invest a lot of attention in the issue, which also makes them potentially more sporadic and short-lived, though they can potentially evolve into new, related ad-hoc publics (Bruns & Burgess, 2011). The significance of ad-hoc publics relies heavily on experiences of momentary connectedness as it manifests in interconnected networks of curated information flows.

The concept of issue publics, at least in the age of online digital media, enjoys a fairly flexible centre position in the triaxial model, not overly determined by any of the six end-points. Firstly, social media as an example have been noted to possess the capacity to easily generate issue publics with the risk of being too superficial and end up hindering potential political motivation (Rathyanke & Suthers, 2018, 8), but also capable of creating positive feedback loops that provoke members of the public to become increasingly engaged with the issue (Obar, Zube & Lampe, 2012). Thus, issue publics can reside in multiple spots on the engagement versus ignorance axis in the triaxial model. Secondly, it is also open to both *aggregation*, as when digital tools are used for sharing and signing petitions (Bimber, 2017), but also *deliberation* in cases where the online environment provides the space for initiating debate and helps the public to develop (Bruns & Burgess, 2011). Lastly, one might attribute a slight tendency for an issue public to drift toward agonism over consensus exactly because of its parochial and often personal nature, seeking to posit the greater importance of its own issue over that of others.

Networked Publics and Data Publics

The concept of networked publics has been created as way to update the theoretical understanding of the public in a world dominated more and more by online digital media. The main characteristic of the concept lies in the name itself, that publics, in terms of a body of people, are *networked*. Publics should be seen less as a purposeful congregation of a designated group of actors, and more as random, spontaneously amassed crowd of people in crosscutting networks (Bennett & Segerberg, 2013). It is important to emphasize that these networks are best described as digitally enhanced rather than implying that their existence are conditioned on digital technology. Opinion formation in the general public has been referred to as happening in complex networks before the web 2.0 revolution (e.g. Habermas, 1996, 307). Still, this digital enhancement of networking practices, most prominently facilitated by social media, makes the concept of networked publics necessary as earlier conceptions of the public become increasingly insufficient for analysing the online media environment (Rathnayake & Suthers, 2018, 2). Networked publics are 'called into being' in ways that are much more varied than before social media. They are relevant both in response to either a specific issue (see issue public) or a broader political trend (Papacharissi & de Fatima Oliveira, 2012, 268). Some of the primary characteristics worth highlighting are 1) the blurred boundaries between public and private and 2) the collapsing of social contexts (Baym & boyd, 2012; Marwick & boyd, 2014). Both aspects relate to how individuals negotiate their own social role in different situations. Additionally, this also relates to how increased mediatization beckons more reflective performances in people's daily conduct, as was mentioned previously in this chapter. One might present oneself differently to one's co-workers, putting on more of a calibrated performance, which is sometimes referred to as the frontstage, compared to being alone or with immediate family, where one's behaviour resembles the more authentic backstage (Goffmann, 1959, 97). While online digital media afford the individual increased control over the information selection, they also create a confluence of spaces. As online networks gradually become more complex so does the difficulty with which the individual negotiates her own role at a given time (Papacharissi, 2010, 68). In a hypothetical situation a person might think: 'If I post this online am I a parent or an employee?' A consequence of these collapsed contexts is the much more fluid position that an individual inhabits in being able to move in and out of multiple publics on different levels. The fluidity of roles and positions that individuals obtain in each other's networks leads to more potential communication with *imagined audiences* (Litt, 2012). These imagined audiences are best realized in public and semi-public settings. Using a social media platform to write a private message to a friend does, of course, not cause any real ambiguity in terms of who is in communication with whom. It is when posting a post on one's Facebook wall, making a comment to a piece of news on a public page or using a hashtag on Twitter that one's audience becomes largely imagined. When joining a discussion using a popular hashtag on Twitter one can imagine that one's tweets are being viewed by tens of thousands of people or all of one's followers while it may actually be that not a single other person is paying attention. Each individual's communication choices will be guided by implicit or explicit expectations about the audience she will reach. Audiences are then, of course, both real and imagined, but navigating the boundary between the two has become increasingly complicated (Gruzd, Wellman & Takhteyev, 2011). This is also why a private person with a small immediate network can unintentionally cause a trend that sends ripples through the greater mass of interconnected networks (Rose, 2017). One of the consequences of these imagined audiences, which ties in well with previously mentioned expression effects and the non-transactive acts of communication in momentary connectedness, is the actual audience becomes less relevant. For example, 50% of Twitter users report not thinking about a specific audience when tweeting (Litt & Hargittai, 2016).

Networked publics are born from the interconnection of ego-centred publics, which describes how digital networking technologies are very much centred on the individual (personalization), but still potentially connected to a diverse world of opinions and knowledge (Latour et al., 2012). Based on the idea of ego-centred publics information sharing in social media networks can be described as *intradiverse* (Seargeant & Tagg, 2019). Social media, in general, offers a high level of information diversity, but is restricted by the immediate (ego) network around the individual, which determines a great deal about how flows of information are curated. The way that networks are centred on an individual, but still part of a larger mass of interconnected networks beckons the distinction between strong and weak ties (Granovetter, 1973). On a basic level most people have both a small number of strong ties, typically as immediate family and close friends, as well as a larger portion of weak ties consisting of colleagues, casual acquaintances and the likes. A large-scale study of Facebook showed that people communicate most with their strong ties, but that weak ties are responsible for bringing novel information into a person's ego-network (Bakshy, Marlow, Rosenn, & Adamic, 2012). The political significance of weak ties will be discussed later in the next chapter.

In relation to the triaxial model, it is worth noting that while networked publics as a concept is open to varying degrees of consensus, agonism, deliberation, aggregation; networked publics provide unique opportunities for political opinion formation that requires lower levels of engagement. In her analysis of affordances for networked publics boyd (2010, 46) notes that activity on online digital media platforms is recorded and does likely persist for longer durations while also being more scalable and easily replicable compared to analogue media. Embedded in the DNA of networked publics is the potential for opinions to go viral, spreading very quickly across vast, interconnected networks having great effect compared to the low amount of effort demanded of the individual (Bennett & Segerberg, 2012, 761). Some have even considered this exponential sharing of content as a new political discourse in itself (Graeff, 2016).

The concept of data publics is built on the idea that online digital media facilitate new kinds of networked publics. Data publics assume the same affordances noted by boyd, but the term narrows down the general concept by focusing explicitly on how the public can leverage datafication, which is a natural part of online digital media (Milan, 2018). The huge quantities of digital traces that are being produced by interaction in complex networks are not just stale records, and a potential method of surveillance (Lyon, 2016), but provide feedback to the individuals in their interaction with the system (Jensen, 2013). Seeing one's own actions such as likes, shares or retweets visually represented and tallied alongside those of others is what Milan (2018, 515) refers to as machines of visibility and agency. This is where data publics can be seen as an extension of networked publics, as it is only in the multiple folds of networks that digital traces can produce a sort of 'distributed agency' (Rammert, 2008). Digital traces involve both individual, performative expression and identity building, but what constitutes a data public is when the sum of all actions becomes visible and fosters collective self-reflection that can serve as a basis for future acts (Reigeluth, 2014, 250; 244). For this reason, the extension of networked public into data public follows an aggregative logic (Juris, 2012), though this does not imply that its enactment is necessarily shallow and not meaningful. Thus, while being enabled by similar affordances as in networked publics, data publics favour aggregation over deliberation.

Affective Publics and Acclamation Publics

This section presents two final conceptualizations of the public, the recently popularized affective public and the much less known, but useful *acclamation public*. The two concepts are closely related through their emphasis on publics that are formed on the basis of emotion and mood rather than concrete ideas and rationales.

Affective publics are mobilized and identified through the expression of sentiment among their members (Papacharissi, 2015). The concept builds on the premise that, on multiple levels, emotion and affect plays a significant role in cognition and guides people by making certain pieces of information more salient than others, which helps form opinions and make decisions (Damasio, 1994). It is worth adding that affect becomes even more significant in situations where an individual's cognitive surplus is low, meaning low levels of knowledge pertaining to the situation with not enough resources to gain said knowledge, or when decisions need to be made quickly. Through the expression of sentiment that resonates with each member of the public people are brought together in unison that can potentially translate into collective power. The idea of affective publics is closely tied to the evolution in public sphere theory away from reason-centred, Habermasian conceptions of the public towards more inclusive notions where passion is seen as important for democratic consciousness, as was mentioned in the previous chapter.

One notable consequence of affect being the foundation of a public is that it becomes perfectly liminal (Seigworth & Gregg, 2010, 9). This means that affective publics can be both a powerful force or vanish as quickly as they came if affect is not strong enough to foster continued mobilization. It is easy to imagine; an expression of sentiment can have deep roots to some fundamental political grievance, but it can also just be a case of people letting off some steam, getting some small frustrations off of their backs. This liminality resonates well with the earlier mentioned notion of momentary connectedness and its inherent polymorphic character, and in the same way affect can sustain a quasi-continuous form of togetherness, meaning that even though no concrete political movement has begun to move forward, the flame is being kept alive through the active manifestation of affective publics.

It should be noted that Papacharissi, who is the main proponent of the concept of affective public, has explicitly linked it to countering dominant narratives of social media technologies. Affective publics are born from networked publics and are intricately linked to the visibility they attain through the digital footprints they leave behind. From this they produce disruptions of the political order and provide visibility to underrepresented viewpoints (Papacharissi, 2016, 311-312; 318).

The term acclamation public is coined by Dean (2017) and is adapted from Agamben's concept of acclamation, which is broadly defined as a public rite with performative elements such as applauding, waving flags, raising hands etc. A central part of acclamation is an emphasis on the institutionalization of the performative dimension. Acclamation acts can be carried out without much reflection on the part of the individual about the meaning and political significance of it (Dean, 2017, 420). It expresses collective affect rather than private feelings; the act of people using a trending hashtag on Twitter together draws a clear parallel to traditional acts of acclamation in its enunciation of the publicness and co-presence of people. Acclamation publics on social media do differ from traditional forms of acclamation by way of voice. There are more degrees of freedom in terms of individual expression in acclamation on social media (Papacharissi, 2015), and thus the public is more pluralized and atomized, but still together through the participation of the ritual (Dean, 2017, 426). This resonates well with the earlier mentioned concept of personal action frames, where an open signifier like a slogan or a symbol can create the context for people to be connected while maintaining their personal narrative (Papacharissi, 2016, 314). In acclamation publics this open signifier can also be construed as a socially institutionalized ritual such as the posting of selfies (Dean, 2017, 427). Affective and acclamation publics can both be tied to the idea of public will; what the public really wants free from discursive restrictions and formalized procedures. This idea is not novel though. In fact, Habermas' bourgeois public sphere is grounded in opposition to the uncritical formation of public opinion, much cherished by Rosseau, where direct expression of the public will is considered the most important (Habermas, 1962/1989, 96). It is easy to accuse affective and acclamation publics of simply being a naïve repositioning the public will as such, however it can likewise be considered appropriate that current media environments warrant this kind of repositioning. Social media has greatly increased the influence the public has on the information flow as well as the complexity of modes of participation.

In the triaxial model affective and acclamation publics favour ignorance over engagement since they can be based on affect, emotion and ritualized social practices, which can be considered less demanding than thinking deeply about issues and formulating long arguments, though there is still room for people to grow in their engagement within and with the public itself. Affective publics in particular are heavy on agonism with little room for consensus as expressions of affect are geared towards showing discontent with the political opposition rather than trying to transcend differences. Affective and acclamation publics afford aggregation as they gain visibility through the digital traces. Though there is less emphasis on exact quantification of opinion compared to data publics.

This chapter has positioned social media as highly participatory communication technologies where the information flow can be viewed as the result of networked curation practices including strategic, journalistic, personal, social and algorithmic forms of curation. Concepts such as ad-hoc issue publics, data publics and affective publics describe public opinion in a manner that lends itself to novel combinations of aggregation and voice as well as ignorance and engagement, although they seem to favour agonism over consensus.

The following chapter examines the political effects of seeking, consuming, sharing and discussing opinions online. The purpose is to better grasp how curated information flows and social media specific enactments of the public relates to the development of individual political knowledge and identity. The focus is specifically on the potential for people to exchange opinions and find common with those whom they do not politically side with as well as the possibility for increased political polarization.

Chapter 3. Political Engagement and Consequences

Everyday Political Engagement and News Consumption

The purpose of the chapter is to locate the political consequences of opinion forming activities as they take place on social media platforms. Social media in relation to political communication has received much attention from the research community, and it is important to specify the kinds of engagement that are most relevant for this thesis. The most popular strands of research include those that focus on how social media can support behaviours associated with activism (e.g. Crivellaro et al., 2014; DiSalvo et al., 2008) or how the platforms are being used to purposefully support formal politics (e.g. Tarta, 2014; Foth, Agudelo & Palleis, 2013). It is important to re-state that the focus of this project is the general public. Making strong assumptions about the types of spaces and discourses that are for gauging political engagement would become too limiting. While the focus on public Facebook pages for the empirical study already poses some serious limitations, it is important to at least consider a broad range of spaces, people, discourses and contexts within these limitations. Thus, theoretically this thesis aligns with previous research into everyday political talk, where the connection to real political effects can be more difficult to locate (Wright, Graham, Sun & Wang, 2016). The focus is on how people casually and sometimes randomly engage with political content and initiate discussion in their everyday lives. One of the primary motivations for this focus is the assumption that political talk, in any shape or form, serves as a cornerstone in democracy (Graham & Wright, 2014) and bestows vibrancy upon the public as such (Delli Carpini, Cook & Jacobs, 2004, 321). Even casual conversation that is not politically framed can have political value (Kim & Kim, 2008). Social media have been viewed as being particularly good for increasing everyday engagement with politics compared to earlier where engagement may have been clearly defined, but also more sporadic (Highfield, 2017). It implies a subtle Deweyian perspective, focusing on the cultivation of the electorate rather than communication that leads to overt manifestations of power, such as protest actions. Political talk can provide a cognitive surplus that is only realized at a later point, such as in elections (Shirky, 2010).

It is nearly impossible to suggest any direct link between very small, everyday acts of communication and actual political outcomes. Furthermore, scholars are usually hesitant about proposing normative criteria such as the triumph of one policy or party over another as a sign of a politically efficacious electorate. For this reason, the object of study is usually the development of individuals and their political engagement. Most studies are based on surveys and hypothesize correlations between the use of social media and political engagement measured as political interest (Bertot et al., 2012), political knowledge (Bode, 2015), political efficacy (Chan, 2016) or offline forms of political participation such as contacting local politicians and organizing protests (Kim et al., 2016). Findings are mixed with a favourable edge towards positive links between using social media and being more politically engaged (See Boulianne, 2015 for review). Additionally, there is evidence sourced directly from social media and discussion forums where expression of interest and promotion of concrete political action develop out of spontaneous talk, the limitation here being that it is difficult to follow up and verify whether political effects linger with people after they leave the discussion (Graham, Jackson & Wright, 2016). Studying political participation accordingly suffers from the same problem mentioned several times already, namely a lack of concepts that denote online participation per se without relying on an offline mirroring effect (Vissers & Stole, 2014).

Central to the emphasis on everyday political engagement is the assumption that discussion spaces as well as people's motivations are not necessarily geared towards politics. Visiting an online group dedicated to sharing parenting advice or browsing one's social media news feed is not motivated by political goals, but the communication can quickly take a political turn (Wright, 2012, Linaa Jensen, 2014), and even cause 'accidental political mobilization' (Hamilton & Tolbert, 2012). Graham, Jackson & Wright (2016) have even demonstrated how political talk in non-political online spaces has a tendency to be less polarized and uncivil, when compared to debates that are politically framed from the start. Political talk can easily occur, but the spaces themselves are not overtly political or encourage political discussion. They are often referred to as "third spaces" (Ibid.). The occurrence of political engagement in non-political context ties in well with the notion mentioned earlier that primary pursuits on social media are personal and social. Thus, political engagement does not necessarily spring forth from identification with a specific ideology, party or political line, but from issues relating to the self and everyday experiences (Ibid.).

For this thesis it is appropriate to conceive of everyday political engagement as happening around a piece a news that a person becomes exposed to which then potentially facilitates further engagement from inside that person's network. Such a piece of news can be from a media organization, alternative media sites and bloggers or simply a personally relayed rumour. Social media has come to account for a large proportion of people's exposure to news, both hard and soft (Boczkowski, 2018). A useful view of everyday political engagement in the context of news consumption is the OSROR model as presented by Chan (2016), which fits well with the curated flows framework explained in the last chapter. Political engagement potentially follows five steps: First is the *initial orientation*, which denotes the general boundary conditions for what kinds of information can be received such as general demographics (e.g. education, income, race and related socio-economic ,measures are all factors that influence what news people consume (Jung et al., 2011)). A more social media-specific description of initial orientation is by how people are embedded in interconnected networks (Thorson & Wells, 2016). Second is *stimuli* where a person encounters or is exposed to a certain piece of news, which can be either intentional or unintentional (Kim, Chen, & Gil de Zuniga, 2013). Third comes *reasoning* which entails engaging with the news content, interpreting the message and maybe even commenting on it, which can be considered a more powerful act of reasoning vis-à-vis expression effects, as mentioned in previous chapter. The fourth step has to do with *political efficacy*, which signifies a change or reinforcement of an individual's own opinion and perception of ability to participate in political discussion and activities (Delli Carpini, 2004), which often leads to the outcome that the person becomes more willing to engage with political content at a later time again (Beaumont, 2010). Last is *response* where people choose to take more concrete action (e.g. starting petitions, protesting, contacting politicians, join political parties etc.). In many cases people might not get further than step one or two, but the five steps illustrates the potential trajectory that can be realized when news exposure is made possible.

News consumption in general has been positively linked to political participation (e.g. Gil de Zuniga et al., 2012), but sometimes only when mediated by conversation (Kim & Chen, 2016) or expression effects (Chan, 2016). At this point it is worth re-highlighting the importance of expression effects as distinct from conversation effects. Conversation over political news in the traditional sense is of course still widespread (e.g. face-to-face, phone calls, instant messaging), but typically as one-to-one or one-to-few forms of communication. Most forms of many-to-many communication that occur in public social media settings do not support conversation in the traditional sense. Many studies claim that social media is better at information dissemination than facilitating conversation (Moe & Larsson, 2011; Brooker et al., 2015). And the users themselves do not even find social media to be suitable for engaging in real conversation (Seargeant & Tagg, 2019, 47).

Communication via comment threads and click interactions (i.e. likes on Facebook) has to viewed as something distinct from traditional forms of conversation and deliberation. Instead people's sense of being part of a public relies on expression effects and the visibility afforded by the digital platforms as described in the earlier mentioned concepts of data publics and affective publics.

Selective and Incidental Exposure

Current and following sections will explore in detail the political consequences of the curation practices that affect the enactment of networked publics. In the arena of everyday politics facilitated by social media it is, as was noted in the previous chapter, flows of information through personal, social, strategic, journalistic and algorithmic curation practices centred on preference-based mechanisms that give form to the range of potential effects. The assumption is that individuals will consume information that reinforces current beliefs or nudge them in a direction that builds on existing feelings of a highly personal nature (Stroud, 2011; Stroud, 2017). The underlying danger is that public opinion will become guided by the consumption, sharing and discussion of information within networks that are increasingly homogenous making it difficult to find common grounds between political oppositions and leading to polarization in society.

This section takes the first step into the discussion about the concern that public opinion formation on social media generates political homophily and polarization by first considering how users become exposed to political information. The study of selective and incidental exposure has existed as a subfield within media studies for some time but is not always related to curation practices that are centred on political preferences. At the same time a separate area of research that focuses specifically on political homophily and polarization as a result of social and algorithmic biases has emerged within the last decade, which only occasionally considers the literature on selective and incidental exposure. This section provides a review of the most relevant findings related to selective and incidental exposure, and the following section will continue the discussion about curation practices centred on political preferences by reviewing the research related to the consequences of political homophily and polarization on social media.

Initially, the rise of complex networks of information flow has prompted the narrative that online digital media lead to increased democratization and thus greater diversity of content (Benkler, 2006). The aggregate effect of curated flows and their different intersections do not produce a black and white picture, which is why a central topic in media research focuses on the dynamic between *incidental* and *selective exposure.* The former happens when people incidentally stumble upon information that they had not looked for or consciously expected to find (Frensch, 1998; Tewsbury et al., 2001), whereas the latter describes situations where people have sought to be confronted with certain kinds of information (McPherson, Smith-Lovin & Cook, 2001; Gentzkow & Shapiro, 2011). The underlying assumption is that selective exposure provides information that aligns with an individual's current opinions while incidental exposure typically has a higher probability of containing counter-attitudinal content. The potential for social media to foster both incidental and selective exposure is appropriately framed by Eady, Nager, Guess, Zilinsky & Tucker (2019) as respectively related to information supply and demand. The supply side is characterized by an abundance of diversity where dissonant viewpoints are encountered incidentally on a regular basis (Brundidge, 2010; Wojcieszak & Mutz, 2009), but is held in check by the demand side where preferred perspectives are easily selected and unwanted ones filtered out (Himelboim et al., 2013). Overall there is not one predominant trend in the literature. Greater opportunity to select and pre-select streams of information does not automatically entail less exposure to other things (Webster, 2014; Beam, 2014; Flaxman, Goel & Rao, 2016). Some results have shown a propensity for selective exposure among most people (Garret & Stroud, 2014), while other studies have only demonstrated strong effects within small groups of partisans (Prior, 2013). At the same time, incidental exposure to diverse information does happen a lot on social media (Morgan, Shafiq & Lampe, 2013), and results have shown incidentally occurring information to have a larger presence in the daily lives of people who use social media compared to those who do not (Fletcher & Nielsen, 2018). One potential explanation is that the media trend towards increased choice of content was already going strong before the popularization of the internet (Prior, 2007), and it is possible that while online digital media provides ever more self-selection the supply side is equally boosted resulting in higher net incidental exposure for people who use social media compared to those relying mostly on traditional mass media. One can easily imagine how choosing to be exposed to only a small selection of TV and radio channels might deliver much less incidental exposure than the networked information flows on social media, which might be attributed to evidence that people who use social media frequently have larger as well as more active and diverse networks (Barnidge, 2015). As mentioned earlier, within the full range of curated flows on social media, users only have partial control over their information environment. If someone watches an entertainment program, and turns off the television when it is finished, it is almost certain that no exposure to unsought political information will have occurred. However, on social media someone might log on just to write a quick personal message but end up seeing a lot of extra information in the news feed. This is backed up by reports that only 16% of users use social media primarily for finding political news, while 70% end up engaging with it (Thorson & Wells, 2016). Additionally, 60% of Facebook users say they encounter political news mostly by chance (Matsa & Lu, 2016). It is a bit more difficult to investigate the degree of attention that users pay to incidentally occurring information in their everyday lives, however it should be safe to assume that at least a minimal impression is elicited, sort of like commercials (Lu et al., 2018). Empirical experiments have also shown that people are able to recall incidentally occurring information (Lee & Kim, 2017), though the evidential strength is limited because it is obtained from a controlled environment.

Selective and incidental exposure in the research literature is, respectively, often associated with conscious choices about consumption of media content aligned with pre-existing (political) attitudes and randomly stumbling upon counter-attitudinal information. However, it is important to remember that those two descriptions only account for half of the story. People can both consciously seek out messages that are aligned with pre-existing views and coincidentally stumble upon diverse perspectives as well as wilfully wanting counter-attitudinal content and accidentally consuming biased information.

The Causes and Consequences of Political Similarity and Dissimilarity in Opinion Formation Processes

Opinion diversity versus opinion homogeneity is front and centre on the research agenda for political communication on social media (Shah, McLeod, Rojas, Cho, Wagner, Friedland, 2017). With curated information flows being centred on political preferences, the main concern is that people become surrounded with politically homogenous information triggering greater polarization between groups in society (Colleoni, Rozza & Arvidsson, 2014). In this sense, polarization is often used to characterize two groups that are opposite each other and growing more extreme in their diverging opinions over an issue, and since societies have multiple issues, political polarization does not necessarily entail that all of society is being divided into just two camps, though this can still happen to some degree (Goel, Mason & Watts, 2010). Links between group homogeneity and polarization are often ascribed to people becoming angrier and more poorly informed over time (Lee, 2016) in part due to the fact that it prevents misinformation from being stopped or challenged (Read, 2016). Information networks that become very homogenous are often described as echo-chambers (Sunstein, 2018), meaning that the sharing of information and exchange of opinions happen only between actors in networks that are so tightly closed around themselves that they are simply echoing the same opinions, with which the whole group already agrees with, over and over without much new information being added. Such political polarization can cause different groups of people to have entirely different realities, which in turn limit the capacities for democratic problem-solving (Yeginsu, 2017). Indeed, polarization caused by social media has been blamed for preventing informed public opinion formation (Benton, 2016), which some scholars have linked it directly to populist victories in the last decade (Solon, 2016; Viner, 2016). The concern at the extreme end of the scale is that continued polarization can undermine belief in democracy altogether (El-Bermawy, 2016).

Indeed, evidence does suggest that politics are becoming increasingly contentious and polarized in democratic societies all over the world (Iyengar et al., 2012; Wendler, 2014; Tilly & Tarrow, 2015). The question then is how much of this trend can be attributed to social media and online digital media more broadly? Though, before getting into how previous research has attempted to answer that question, it is important to note that there are many aspects of polarization. First of all, the outcome of political communication can be any of three: polarization, de-polarization or homeostasis, meaning people move further apart, closer together or nothing much happens (Slater, 2015). Furthermore, polarization and related outcomes have psychological, technological, social, empirical aspects, which are necessary to disentangle to be able to grasp the full spectrum of it. Most recent literature on the subject tends to ignore this or focus on just one aspect of polarization. This thesis will attempt to trace the different aspects of polarization (and de-polarization) through the different modes of coming across information that was briefly outlined at the end of the last section. Exposure and potential engagement with information can be both intentional and incidental, while the content itself can be aligned with pre-existing beliefs or be counter-attitudinal.

Intentional selection of politically similar information occurs most obviously at the personal and social level when people consciously choose to connect to fewer actors or channels because they feel that only those few provide them with a resonant and singular message, or because others, including friends and family, are identified as the cause of cognitive dissonance in the form of stress, uneasiness or social ambiguity and are avoided as a result (Stroud, 2010). This avoidance of other people is of course linked to the idea of *the spiral of silence* (Noelle-Neumann, 1974) with the key difference that, on social media, instead of reacting with silence, people can make a greater effort to select and engage content outside of certain perceived hostile environments (Quercia & Crowcroft, 2013). Some minority of people who are strongly partisan even view balanced content as harmful and will seek to avoid it altogether (Mcleod, Wise, Perryman, 2017). While intentional selection, of course, is centred on personal and social curation, it is worth noting that journalistic and strategic curation also play a potential role. Politicians and journalist can seek to double down on people's search for less ambiguous messages by appealing to more narrow and extreme audiences (Conboy & Eldridge, 2018).

It is important to keep in mind that people are motivated to seek out and generally wish for more politically dissimilar information (Conover, Searing & Crewq, 2002)[11]. In fact most people by far claim that a balanced news diet is preferred to one that is only in line with pre-existing beliefs (Garret & Resnick, 2011), though news where the content is balanced is also preferred over messages that are directly counter-attitudinal (Feldman et al., 2013). Motivated reasoning theory argues that the intentional search for information is grounded in two types of motivation: validation and accuracy (Kunda, 1990). The former describes the longing for information that can bring some certainty to one's pre-existing views, while the latter is a search for information that can challenge one's views and give a sense of being closer to some empirical truth. In this regard, balanced news might be the best to deliver way to deliver on both motivation fronts. Here it might be good to highlight previously mentioned weakness of the curated flows framework, which focuses mostly on exposure and distribution. A balanced news diet can be provided both by being exposed to equal amounts of news pieces with opposing viewpoints, but a single news piece can also have greater content diversity in itself (Bozdag et al., 2014).

The unintentional selection of politically similar information might be the one that has received most attention in recent research on social media and polarization. Though this is rarely done in the literature, it is convenient to distinguish between the social psychological side of the issue related to personal and social curation and the technological one. The social psychological side of it is often attributed to an effect called confirmation bias, which is often used in a broad sense to describe people's preference towards information that confirms their views (Knobloch-Westerwick & Kleinman (2012). However, it is worth emphasizing that the effect does not describe people's intentional selection of content, but rather an unconscious predisposition to pay attention to and internalize information that is consistent with already existing

[11] A caveat with this sort of research is that respondents might be more likely to want to appear motivated to seek out politically diverse news even though their actual motivation to do so is significantly lower.

narratives about the world. It is an effect that unintentionally directs attention towards and retention of information. Coronel & Poulsen (2018) did several experiments in which the test subjects had to read, remember and then pass on information to other test subjects resulting in information being incrementally changed over several iterations until it better fitted the views that were considered more mainstream among the group. Thus, confirmation bias is best considered a social psychological effect at the unconscious level (Hendricks & Hansen, 2014).

The technological side of the unintentional selection of politically similar information is primarily located at the level of algorithmic curation and has been most famously expressed as the tendency towards *filter bubbles* (Pariser, 2011; Pariser, 2015). As mentioned earlier, online digital media function as digital intermediaries and are sustained by algorithms that help users find and select information. Filter bubbles can happen when the main digital intermediaries (e.g. Google, Youtube, Facebook etc.) recursively curate information that people are more likely to find interesting, which, together with confirmation bias effects, can cause people to be trapped in bubbles of software filters (algorithms) that allow for less and less diverse information. The opaque algorithmic bias inherent in online digital media has become one of the main points of critique of social media as a less than ideal platform for democratic opinion exchanges (Gillespie, 2014) with filter bubbles potentially transforming into echo-chambers (Sunstein, 2018). However, a seminal study by Bakshy, Messing & Adamic (2015) showed personal curation and confirmation bias to be a stronger effect than algorithmic in determining exposure to political news on Facebook, though there are still limitations to their methods[12]. It is also worth keeping in mind that it is easier to blame a piece of technology than people and social structures (Seargant & Tagg, 2018, 42). A theoretical argument against filter bubbles as the predominant cause of echo-chambers is the previously mentioned notion that social media practices arise from the interplay between people and technological affordances. Thus, people start to form expectations about the algorithms that control their news feed and adjust their actions accordingly (Jones, 2015). This argument also has some empirical backing from evidence that shows a significant increase in how aware people are about algorithmic biases and their potential effects

[12] The researchers behind the study were at the time part of Facebook's internal research unit, which is a cause for concern about potentially biased results. It is at least imaginable that Facebook would not want to publish research that would put their platform in a negative light.

(Dylko, 2016).

Before moving on it seems appropriate to quickly reiterate the premise of algorithmic biases. At the basis level digital intermediaries, which are commercial companies, thrive on user activity, typically to generate more advertising revenue. For this reason, the sorting algorithm's main responsibility is to show users types of content that they are most likely to respond positively to or engage with, thus encouraging them to stay longer on the site or return more frequently. Most research in political communication tends to focus on the part of the algorithm that makes selections based on previous user activity, meaning similar content or sources. However, Nikolov, Lalmas, Flammini & Menczer (2019) note that most search, filtering and news feed algorithms are also tuned to show content that is generally popular or 'trending'. They consider algorithms to have both a homogeneity bias and a popularity bias. While all the major digital intermediaries (Google, Facebook, Twitter, Youtube, Wikipedia etc.) deploy algorithms that have both biases, the results of their particular study then show that search engines such as Google have a stronger popularity bias with social media having a stronger homogeneity bias. The important point here is that attaining influence in networked communication on social media also depend on whether a message or its sender can create shock and awe with some mainstream appeal, akin to what has been referred to as sensationalism in mass media (Örnebring & Jönson, 2004).

Last but not least, it is worth considering the unintentional selection of politically dissimilar information, which is often the implicit focus of studies of incidental exposure as laid out in the previous section. Studies of information dissimilarity and incidental exposure on social media tend to put emphasis on the level of social curation (Bennett & Segerberg, 2012). The opportunity to encounter diverse and politically dissimilar information is often attributed to the special role that weak social ties have on social media (Eady, Nagler, Guess, Zilinsky, Tucker, 2019, 19). People are generally made more aware of their weak ties on a day-to-day basis in a way that was much less prominent before social media (Kwon, Stefanone & Barnett, 2014). Of course, this means that the actual diversity of one's social network can be a big factor in how politically dissimilar one's exposure to information is, which is why network size and frequency of social media are strongly correlated with amount of incidental exposure (Bechmann & Nielbo, 2018). The importance of weak ties can be explained with the notion that social networks on social media are often determined by people's life trajectory rather than by their concrete political preferences (Seargant & Tagg, 2019). This resonates well with earlier mentions that people use social media primarily with personal and social goals in mind. This, however, still has an upper limit of exposure diversity because social networks tend to be more homogenous than perfectly random networks, so-called 'superdiverse' networks (Androutsopolous & Juffermans, 2014). Instead there is actually an observed trend for online and offline social networks to become increasingly isomorphic (Rojas, 2015).

Some studies focus entirely on the social psychological effects of social media, namely as an enhancer of known dysfunctional social dynamics (e.g. Hendricks & Hansen, 2014), while some consider mostly the technological aspects related to algorithmic biases and filter bubbles (e.g. Bozdah, 2013). Although, on the whole, most research, implicitly or explicitly, combines both psychological and technological aspects in their study of preference-based curation and political polarization, which has so far produced mixed findings. There have been large-scale Big Data studies showing clear tendencies for polarization (e.g. Barberá, 2015; Mocanu, Rossi, Zhang, Karsai, & Quattrociocchi, 2015; Schmidt et al., 2017) as well as those that show only limited polarization effects and overall much more diverse large-scale behavioural outcomes (e.g. Barberá, 2014; Bakshy, Messing & Adamic, 2015). The story is the same with qualitative studies where some show that users are much more likely to share, read and remember news messages with which they already agree (e.g. An, Quercia, Cha, Gummadi & Crowcroft, 2013; Grevet, Terveen & Gilbert, 2014), while other studies reveal relatively high willingness among users to consume and engage with news that are diverse and even counter-attitudinal (e.g Semaan, Robertson, Douglas, & Maruyama, 2014), especially when conditioned by how the content is presented (Graells-Garrido, Lalmas & Baeza-Yates, 2015).

The great quantity of studies into political polarization on social media, which have produced mostly mixed findings, have led some scholars to conclude that a total schism between, on one side, rife polarization, filter bubbles and dangerous echo-chambers, and diverse, politically productive networks on the other, might not be the best; instead more precise conceptualizations of polarization and de-polarization are needed (Haewoon Kwak, Posegga, Jungherr, 2019). This thesis will thus follow the same line of thinking, namely that social media can initiate and promote increased exposure to both similar and dissimilar news, also with the possibility of being both intentional and unintentional. This is not to dismiss effects such as filter bubbles and echo-chambers. They should both be considered real, highly relevant consequences of social media use. However, it is not hard to imagine, that they can happen under some set of specific circumstances, while not being able to manifest in other situations. Some studies, for example, report budding echo-chambers as a kind of local effect within an ecosystem that is largely diverse (Eady, Nagler, Guess, Zilinsky, Tucker, 2019). Research from the United States has also suggested that polarization does not happen uniformly across the political left-right spectrum, although the results are disjoint with one study blaming right-wing conservatives for being the main drivers of political polarization (Parker & Baretto, 2014) and another study pointing to left-wing liberals as less open-minded in relation to exposure and discussion online (Beam, Hutchens & Hmielowski, 2018).

This project seeks to focus the automatic measuring of public opinion on effects related to political homogeneity/heterogeneity and polarization/de-polarization. This is both to map potential polarization processes in the public on social media, but also to demonstrate the usefulness of tools that can make effects of political homophily and polarization more transparent as the opinion formation process is occurring, thus combating some of the obscurity that indeterminate combinations of curation biases have brought to public opinion as it takes form on social media. This is radically different from most previous attempts to automatically measure public opinion on social media that often focus on predicting poll results (Jungherr, 2016) or estimating what the public thinks about a topic using simple measures such as aggregated positive versus negative sentiment (Cody, Reagan, Dodds & Danforth, 2016). The next section will extend the discussion of political polarization to cases that focus on critical reception and discussions about politically disagreeing content rather than just the finding, sharing of information, which has been the main focus in the last two sections.

Political Disagreement Beyond Exposure

The previous section gave an account on a central topic in political communication on social media, namely political polarization, which is viewed as potentially detrimental to democracy. Most of the research mentioned focused on effects pertaining to exposure to politically similar or dissimilar information with the aggregate of results not showing a clear tendency toward polarization or de-polarization as a result of such exposure. Even though information exposure in curated network flows is already a complicated matter, there is at least another level of complexity that should be acknowledged, which is that individuals have different predispositions and motivations that result in different types of engagement, interaction and discussions. This goes back to a classic notion in reception studies, namely that the way content is presented (its encoding) in conjunction with the cultural and political predilections of the receivers which influence the way a message is comprehended (its decoding) determines the actual effect of the media content (Hall, 2001). Three outcomes are possible: 1) the dominant-hegemonic code where the receiver sees the message as congruent with previous narratives; 2) the oppositional code where the message is largely rejected; and 3) the negotiated code where the receiver accepts parts of the message even if it runs counter to his/her current attitudes. Theoretically, only the negotiated code can result in de-polarization.

A lot of studies, many of them mentioned in the previous section, simply consider exposure to politically similar or dissimilar information to be both the cause and indicator of either polarization or de-polarization. And the overall correlation between very homogenous networks of curated information flows and the development of more extreme views should be considered real and problematic. Though, how people actually react and reflect on exposure individually is not so straightforward. Mutz (2002; 2006), which are two of the most cited works on the topic of people's engagement with politically similar/dissimilar information and disagreement, lay out both positive and negative consequences. Firstly, increased exposure to and engagement with politically similar content might embolden people to participate more in political discourse and identify their democratic duty (Ibid.), which is often, among many scholars of political communication (e.g. Dahlgren, 2009), considered an important achievement in the fight against cynicism and apathy. Increased communication with like-minded others promotes trust (Lewandowski et al., 2012) and can cause mobilization and unity among people (Obar, Zube & Lampe, 2012). Tight networks of reinforcing opinions have been referred to as sorts of 'safe spaces' for fostering political action (Hibbing & Theiss-Morse, 2002). This suggests that maybe some common ground needs to be found among a collection of people for momentary connectedness, which is emblematic of social media, as was mentioned in the previous chapter, to morph into something that has a lasting effect.

Secondly, and likewise, engagement with dissimilar information and disagreement can lead to both positive and negative outcomes. Exposure to and awareness of opposing views has the power to increase political tolerance (Mutz, 2006; Garret & Resnick, 2011) and can in some cases help people to think more deeply about previously held ideas (Price, Capella, & Nir 2002). However, exposure to opposing views can just as likely make people more confused and ambivalent about their opinions with the result of further detachment from politics (Mutz, 2006). Depending on the framing of the content, exposure to politically dissimilar views can be a great source of frustration for people (Smith, 2017). People might also choose to engage with counter-attitudinal content with the explicit intention of mocking it (Jae Min & Wohn, 2018). Findings have shown both negative (Nir, 2005; Mutz, 2006; Lu, Heatherly & Lee, 2016) and positive (Taber & Lodge, 2006; Hogan, 2010; Iyengar, 2012) relationships between engagement with politically dissimilar information and political participation, which is a further attestation to the complicated nature of political consequences of social media use.

Engagement with politically dissimilar information is of course not a uniform experience; specifically nuances in content and people's identity may play a role. It is possible to distinguish between two dimensions of political difference: opinion and partisan. The former, opinion-based difference, has already been touched upon in relation to confirmation bias. It has roots in cognitive dissonance theory, which suggest that a piece of information can cause more or less dissonance with the receiver depending on how much the message differ from prior beliefs and attitudes (Festinger, 1957). A message might be rejected if it falls completely outside a person's 'latitude of acceptance' (Sherif & Hovland, 1961). Partisan based difference on the other hand might have less to do with the content itself and instead depend on the source of information and social cues pertaining to the sender. Social identity theory suggests that only a few social cues are necessary in order for someone to place another person into a political out-group, which can have a large impact on the perception of further communication (Tajfel & Turner, 1979; Tajfel, 1982). There are few non-verbal cues (e.g. body language) in online communication, but language, timing, cultural markers as well as cues about relationships and political affiliation are all important aspects of meta-communication

(Walther, 2011). It is worth recognizing that social media have increased the availability of social cues compared to anonymous message boards of the kind that were more common in the early days of the internet (Antheunis, Valkenburg & Peter, 2010). Since social cues heighten and direct attention when individuals are deciphering information (Westerman et al. 2008), it can be assumed that social media provoke extra strong effects compared to other public spaces on the internet. This however does not solve the conundrum that engagement with similar and dissimilar information can have both positive and negative consequences.

Some solutions have been offered by looking into the details of the content and context of opinion exchanges. The way a message is constructed, both in terms of social cues and other discursive features, can lead to affective polarization. Language choices that make a message overly negative or offensive are more likely to be met with an equally negative response (Kaplan & Anderson, 1973). Similarly, with social cues; negative and polarizing responses are sometimes motivated by purely partisan reasons meaning people dislike opinions for no reason than that they belong to the 'other side' (Abramowitz, 2010; Iyengar, Sood & Lelkes, 2012). All things considered we cannot expect exposure to politically dissimilar information or even heterogeneous interaction to cause de-polarization. Sometimes viewing counter-attitudinal opinions might even cause an increase in polarization (Bail et al., 2018; Theocharis et al., 2016).

One of the most popular suggestions for communication that mitigates affective polarization is to have content that is balanced, consensus-oriented and civil; all three often go hand in hand (Gastil, 2000). Arguments that are civil are considered to be more convincing (Ng & Detenber, 2005) and experimental evidence suggests that civility is a powerful factor in having people be more open to political dissimilarity (Gil de Zuniga, Barnidge, Diehl, 2018), while incivility very often leads to continuous increase of polarization (Anderson et al., 2014). It is still worth noting though, that, akin to how communication with like-minded others can foster unity, trust and increased political participation; incivility and anger can stimulate participation and bring people together (Valentino et al., 2011; Borah, 2014). Similar to civility in messages, effects pertaining to openness to political dissimilarity have been observed in regard to messages that strive to be balanced and consensus-oriented (Babaei et al., 2018). In relation to social cues there is evidence that while people most often prefer strangers who are politically similar, such preference can be highly context dependent. Morey & Boukes (2018) show how people's actual preferences for discussion partners change based on the context (e.g. the topic of discussion). When people do not know the political stance of the people they are engaging with, they are likely to prefer discussion groups that consist of people from different parts of the political spectrum over those that are completely homogenous when considering a range of different contexts.

The literature presented in this chapter should urge us to re-ask the question: "What kind of political engagement is actually good for democracy?" There is a good case against political polarization, especially if continuous communication leads to the formation of echo-chambers. However, at the same time many of the causes of polarization, such as communication in homogenous networks, affects and even incivility, also help to foster the political engagement necessary for people to actually realize their democratic identity. Research continues to claim that more knowledge is needed before answering such a question becomes possible (e.g. Neo, 2019, 152).

Patterns of Polarization and De-polarization in Networked Data Publics

The theoretical framework presented in the first three chapters has served to show how public opinion on social media holds certain novel possibilities based on their potential for combining characteristics relating to aggregation versus voice, agonism versus consensus and ignorance versus engagement. The actual formation of public opinion depends on how the information flow is affected by strategic, journalistic, personal, social and algorithmic biases centred on the political preferences of individual users. The consequences that such preference-centred curated flows have on political engagement and knowledge in the public are fairly complex and context dependent, however the main concern in most of the current literature tends to be the negative effects that increased political homophily and polarization have on public opinion. The purpose of the remaining chapters is to explain the Big Data-oriented methods that have been developed for this project to measure manifestations of public opinion in these curated information flows with respect political homophily and polarization. The purpose is two-fold: 1) measuring the prevalence of homophily and polarization across the Danish public on

Facebook and 2) using the results to discuss how Big Data and automatic computational methods can be used to take advantage of the potential configurations of the public offered by social media (i.e. configurations of aggregation versus voice, agonism versus consensus and ignorance versus engagement) in order to make the opinion process more transparent and visible for the users, as exemplified in concepts such as the data public. This section will briefly summarize some of the key points in the theoretical framework and present the empirical point of departure.

Returning to the evolution of different concepts of the public in response to changes in media and society traced in the two first chapters, the triaxial model can be used to highlight some of the prime characteristics of social media engendered manifestations of the public. Social media allows for new ways of communicating and being together in public, which by extension brings about new modes of being part of a public. The most outstanding change is the mixing and recombination of voice, aggregation, consensus, agonism, engagement and ignorance that have become possible with online digital media in general. With mass democracy and mass media the dominant view became that of a representative parliament, a formal public, connected to the wider informal public, via the free press. Each, respectively, on opposite ends of the engagement – ignorance continuum. Searching for ways that would let the public gain expression, the pre-online era was dominated by ideas of polled publics and mini-publics, each respectively on opposite ends of the aggregation – voice continuum. As has already been touched upon, more recent concepts of the public, such as data publics, allows for more middle positions in the triaxial model.

While the triaxial model oversimplifies many concepts related to the public, it is useful to focus the discussion around its the three axes. Social media most notably offers a bridging of the gap between aggregation and voice. This was illustrated through the concepts of affective publics and data publics that highlight how the expression of sentiments and opinions gain a special status vis-à-vis the digital traces that are left behind by users. The public interaction process itself becomes datafied and thereby potentially aggregated and visualized (e.g. showing number of likes and comments to a Facebook post on the post). Ways of engaging with political matters and expressing opinions on social media are much less restricted than in opinion surveys, but can still be counted, measured and summed up (of course with some loss of complexity). Viral tweets, trending hashtags, Facebook groups and posts that receive thousands of likes, these are all examples of how the micro-actions of individuals become a visible public through the aggregation and visualization of digital traces (Milan, 2017, 5). This thesis will argue that the potential of mixing voice and aggregation in digital manifestations of the public has not been fully realized.

Looking at the primary characteristics of social media publics, they seem to be slightly in favour of ignorance and agonism. While social media can most certainly be used as an instrument by highly engaged individuals and organizations to garner attention and raise awareness, the wider, networked public often use it in ways that are emblematic of momentary connectedness (Rathnayake & Suthers, 2018) and imagined audiences (Litt, 2012) rather than continuous debate and sustained communities. Again, it is important to stress that ignorance is not a negative term here. There is great power in allowing many people to participate in political activities without demanding much engagement from any single person, which has been demonstrated by Bennett & Segerberg (2013) in developing the concept of personal action frames. The loosely organized and potentially spontaneous coming together of people seems best directed by narratives of affect and political grievances. As such, the collective power attributed to the quick and effortless forming of ad-hoc issue publics on social media, however liminal, is most in line with that of an agonistic public to which lending room to unheard voices and showing discontent with dominant ideas or governments is the prime resolve (Papacharissi, 2016). And to reiterate, agonism is not preferred over consensus or vice versa, instead each have their own advantages and disadvantages as was shown in Table 1.0 in chapter 1.

The practical consequences for social media publics with a potential for both voice and aggregation as well as a tendency towards agonism and ignorance can be further illuminated by including insights from media effects research. The concept of a networked public does well in suggesting that publics are called into being through cross-cutting networks, which implies that information flow is networked. The networked information flow on a macro level can be explained with curation logics that include strategic, journalistic, personal, social and algorithmic curation (Thorson & Wells, 2015). Curation logics, in the context of political communication, are centred on the political preferences of social media users, which should then also be considered relevant for the formation of publics. Curated flows of information in social media networks connect the individual to the collective. They are a significant influence on how publics form and who ends up participating, especially when dealing with short-lived ad-hoc publics such as those that form around a single hashtag or Facebook post. If we assume that the formation of publics on social media favours agonism over consensus and ignorance over engagement, how this relates to information flows and users' political preferences then becomes the main issue for how opinions form on social media. From this it does seem to make sense that political polarization, increased social and political homogeneity and the potential spread of misinformation are high on the social media research agenda, at least at the time of writing. It matches the disadvantages of agonism and ignorance in terms of the public being pulled apart into more extreme political positions each contesting the other with some potentially being misled or only aware of one side of an issue. The argument here is not that agonistic politics or concerns over political engagement among citizens in an evolving media landscape is anything new, but rather that these tendencies are being shaped by the networked logics of social media of which users possess means of consuming content and expressing their opinion in ways that didn't exist before online digital media.

The concepts in the triaxial model do not have normative predispositions and whatever disadvantages a certain manifestation of the public might have; they can potentially be countered by its advantages. However, they are still only theoretical framings of the general conditions for different manifestations of the public, whereas opinion formation in practice can be influenced by such advantages and disadvantages to varying degrees. If people feel disillusioned or indifferent after expressing their opinion or interacting with other users on social media, then the advantage that it was easy for them to participate and add their voice to the public is not really felt. It must be possible to trace a positive outcome of people participating in public opinion formation.

Recent research has shown very mixed results when it comes to social media use and political engagement, though there is a slight tendency towards a positive correlation between the two. Studies related to whether people are becoming politically polarized strikes a similar note in that quantitative and qualitative studies have presented evidence for both polarization and de-polarization. However, with respect to exposure to and interactions between politically dissimilar groups of people, polarization is a complex matter. From the material presented in this chapter we can narrow it down to two overall aspects of polarization: 1) polarization as a consequence of networks and communities becoming increasingly homogenous and closed off such as in the example of the echo chamber, and 2) polarization as the reinforcement of previously held views or development of more extreme opinions as a result of exposure to or interaction with people with opposing views. To further complicate the issue polarization cannot be considered a de facto negative phenomenon. Increased homogeneity and reinforcement of previously held views can be considered important elements in political mobilization and development of people's political identity, where even incivility and anger can play positive roles, whereas de-polarization can lead to ambivalence and detachment from politics.

Following these perspectives on polarization it is the argument of this thesis that the triaxial model can be useful for managing the complexities involved in framing manifestations of the public on social media. From the agonism standpoint on democracy it is entirely possible that we actually do want a certain level of polarization to exist in societies. Strong political identities are necessary for the masses to be able to support a coherent hegemonic bloc (Mouffe, 2005). In a similar vein with ignorance and engagement, the liminal properties of short-lived and ever-changing networked publics that are rife on social media can appear to have little political value, however the ease with which they can form can outweigh this dubiety. As Zuckerman writes qua low-engagement aspects of democracies: "it is not supposed to be hard to vote." (2014, 158). The fact that a lot of research shows positive correlations between social media use and political engagement adds further support to the significant advantages that low-entry participation holds.

While the triaxial model might seem to help manage the complexities involved with social media publics it also obscures a suitable point of entry for critiquing the function of the public. It remains difficult to assess the democratic value of the public on social media since there are so many potential advantages and disadvantages to different manifestations of the public. This thesis argues that it is important to retain this complexity and not make a final judgement call on which characteristics are most important for the function of the public. The results presented in the later chapters are relevant independently from what one would consider the most appealing outcomes of opinion formation on social media. However, since the motivation for this project was not born in a vacuum; this thesis will consider a provisional point of entry for critiquing the function of the public on social media, which is explained in the following paragraph.

This thesis takes its cue from the public deliberation tradition and Bohman (2000), who has, among other things, studied the potential for solving seemingly unsolvable dilemmas through democratic means. At the core of his creed is the idea of dialogue. The public can contain disagreement, polarization, radical ideas, peculiar voices and powerful emotions, but without any dialogue democratic cooperation is unlikely to go on (Ibid., 42). Dialogue supposes that people are not just throwing words at each other but listening and responding as well. This basic notion can also be found with Mouffe (2000) for whom the clash between different political positions lies at the heart of democracy. She stresses the importance of not viewing the political other as an enemy, but an adversary with whom ongoing communication is necessary to sustain an informed democratic society (Ibid., 101-102). From this we can make the provisional assumption that too much polarization can be detrimental to democracy since if people are completely isolated in echo-chambers, or not willing to take the opinions of the other side seriously in any capacity, dialogue cannot occur. A more generalized version of this assumption would simply be that any extreme case of either polarization or de-polarization should be considered problematic. Furthermore, while overall polarization contains both advantages and disadvantages, the digital traces of the data public can theoretically be used to make public participation, whether it be causing polarization or de-polarization, more transparent for the public itself. This is the idea of the previously mentioned concept, data agency. It is the argument of this thesis that by taking full advantage of the combination between voice and aggregation made possible by online digital media and using it to make the communication between different political positions more transparent, it becomes possible to promote engagement and knowledge for those parts of the social media public that do not feel confident in personally seeking out information inductively and alleviate some polarization by promoting consensus in publics that are dominated by agonism.

Empirical point of departure

The purpose of this thesis is to create and test methods to evaluate trends of public opinion formation on social media in democratic societies. The methods are best described as Big Data-oriented computational methods and while a little bit of manual data preparation is necessary, the overall framework that they are built around can be coupled directly to the data stream. As such the methods can be automized and the results can potentially be fed back to the public as opinion formation is taking place.

The methods are supposed to capture a significant part of public discussion on social media; specifically, the focus will be on public pages on Facebook. In the grand scheme of things, public Facebook pages represents only a fraction of opinion formation across all avenues of online digital media, however for some countries, especially Denmark, they do cut across many sectors and can at least be representative of some general trends within the public. The methods and ideas behind them, which will be explained in detail in the next chapter, can theoretically be expanded to other platforms such as Twitter, but for obvious reasons such as lack of time and resources, not to mention computing power, public Facebook pages will be the only empirical focus of this thesis.

The methods are designed to pinpoint individual discussions and measure the amount of political agreement and disagreement with respect to political homophily and polarization. Thus, the methods can be used as a tool to find patterns and uncover certain qualities pertaining to a specific debate and the direction it is taking with respect to how politically homogenous the group of participants is and how much cross-cutting agreement it produces. However, since the focus of this thesis is on public opinion formation in general and not a specific political group, debate or topic, the testing of the methods will focus on the very broad trends vis-à-vis political agreement/disagreement and polarization/depolarization across various publics.

This study will depart from previous research by framing cross-cutting agreement and potential polarization in a way that is centred on people's political alignment with concrete party politics of a given nation state, but still allowing some flexibility and accounting for more complexity than most previous studies. This is accomplished in numerous ways. Previous approaches that use computational frameworks for studying polarization and cross-cutting agreement can most often be divided into two categories. The first include studies that try to retain a lot of complexity in the formation of publics, which can result in mappings of all social media interactions within a country (e.g. Bruns et al., 2016) or network analyses that compares clusters of users based on all the pages they have visited (Schmidt et al., 2017) or all the links they have shared (Bechmann & Nielbo, 2018). One of the weaknesses of this approach is that the results can quickly become too abstract to deliver insights on concrete political opinions. This is the case with Schmidt et al. (2017), which concludes that political polarization in the form of increased homophily is likely amplified by social media because most users tend to visit only a small subset of pages. Not all pages have the same political significance though. User activity in neutral spaces that have a high degree of political diversity is very different from user activity on highly politicized pages. The second types of studies are those that consider the political standpoint of users but limited to a binary split. This most prominently include studies of the bipartisan US public (e.g. Lock & Gelman, 2010), but also those that simply reduce political alignment to either right-wing or left-wing (e.g. Conover et al., 2011). Reducing political positions to binaries can be useful to highlight specific trends, however the framework created in this thesis has multi-party dynamics as the basis of the method. Thus, the political position of a given user can always be understood in relation to one or more political parties and not just a right-wing/left-wing construct.

Most previous research, even those studies that apply Big Data approaches, are often confined to a single case, topic or point in time (e.g. Bossetta, Segesten & Trenz, 2018) or they consider only single, fixed instances of political discussions, such as comparing retweets and replies on Twitter (e.g. Bruns, 2019). This thesis departs from previous research by including a longitudinal perspective that takes into account how polarization evolves over time. It also seeks to account for the fact that cross-cutting agreement can have different configurations depending on how a given discussion is progressing. If users are initially split by a political issue but can reach some agreement through the exchange of opinions, then that is different from cases where no agreement is reached at all. Thus, this thesis seeks to account for multiple steps in the flow of a single discussion around a public Facebook post.

Concretely, political polarization/de-polarization will be considered in two forms: either as an increase in political homogeneity, vis-à-vis less communication between people with opposing political positions, or as a heavy disagreement between politically dissimilar groups. Disagreement/agreement incorporates both how polarized users are in their initial response to a Facebook posts as well as how much agreement reach across political oppositions, which can be abbreviated as cross-cutting agreement.

Based on the literature presented in the previous sections of this chapter, this thesis proposes the following hypotheses to guide the analysis:

- H1-A. Public Facebook pages will become increasingly homogenous over time, year by year, thus political homophily will see an increase.
- H1-B. Cross-cutting agreement will decrease over time.
- H2-A. Political homophily will increase from the beginning to the end of a single discussion.
- H2-B. Cross-cutting agreement will decrease from the beginning to the end of a single discussion.
- H3-A. Political homophily will be unequally distributed across different spaces and topics of discussion as well as combinations hereof.
- H3-B. Cross-cutting agreement will be unequally distributed across different spaces and topics of discussion as well as combinations hereof.
- H4-A. Political homophily will be positively correlated with incivility and angry emotional responses.
- H4-B. Cross-cutting agreement will be negatively correlated with incivility.

Multiple steps are necessary in order to accomplish the analysis sought by this thesis. Firstly, a method needs to be developed that can, with reasonable accuracy, predict the political position of individual users who participate in discussions on public Facebook posts. Secondly, an efficient calculation that can evaluate the level of political homogeneity and cross-cutting agreement based on the political position of all users during multiple steps of a public post discussion needs to be developed and tested. Thirdly, additional information has to be added that allows for dividing posts into different categories corresponding to the type of page it is posted on, the topic of the content (e.g. Economy or Gender Equality) and the quality of the text (i.e. the amount of incivility in comments by users). The following chapter will explain the general methodology behind the techniques developed for this study, whereas chapter 5, 6 and 7 will cover the three steps just mentioned.

An important contribution this thesis seeks to make is to propose a computational framework that is more deeply rooted in media theory and public sphere theory, which is something rarely done in the field of computational social science (Freelon, 2014). By relating the results of the study to the theoretical framework presented in the previous chapters, it is the hope of this thesis that knowledge can be added to new directions for research of public opinion on social media.

Chapter 4. Methodology and Data

Big Data and Computational Methods

The purpose of this thesis is to develop and test methods for examining behavioural trends pertaining to public opinion formation on social media with respect to political homophily and polarization. The methodology does not revolve around any particular established methods but employs a range of different techniques to find and analyse patterns in large-scale data. Drawing on and recombining different techniques, as is done for this project, should not be confused with a mixed methods approach. The methodological focus of this study is on quantitative data analysis aside from a few illustrative examples. At the time of writing there no single methodological framework exists that could describe the set of methods as they are used together in this study, however the overall approach is oriented towards Big Data and computational methods.

Big Data has become a methodological point of discussion because of the availability of large amounts of data across many fields of research. Scientific domains such as astrophysics have long relied on huge, multi-facetted data sets (Kithin, 2013). Terms such as Big Data and computational methods in the context of research methodologies, are born out of the 'computational turn' in the social sciences (Berry, 2011), which is in large part due to the proliferation of the internet and ubiquity of digital devices. However, it is important to mention that computational methods are attributable to a certain way of approaching empirical data and are not a bound by data types or technical equipment. For example, the development of software such as NVivo, STATA and SPSS have increased the precision and ease with which researchers engage with interview and survey data, however such techniques do not fall under the category of computational methods. The same can be said about Big Data. Some engineers might simply consider Big Data to be stored collections of information that correspond to x-number of rows in a database or bytes on a hard drive (Tsvetovat & Kouznetsov, 2012, 151). However, in the context of research methodologies Big Data can be characterized by other traits such as granularity and exhaustivity while not taking up more than 10MB of storage space (Kitchin, 2013). And vice versa, data collections that consist of millions of observations with hundreds of features such as national censuses, which have been carried out in many Western countries for more than 150 years, would normally not be considered Big Data (Dalton, 2016). The next section will go into detail about the methodological implications of Big Data-based research and computational methods. Since Big Data is almost always used in conjunction with computational methods they will be referred to as Big Data methods from this point on.

Paradigm, Implications and Techniques

This section will briefly present some of the popular definitions for Big Data and discuss the main impacts that Big Data has had on research design as well as potential pitfalls. Big Data methods do not have a clearly defined set of procedures or rules and there are not yet any common frameworks that can be directly applied to a certain kind of dataset (Mayer-Schoenberger & Cuckier, 2013), though some techniques are seen more often than others. Statistical techniques that were developed many years ago are still applicable to Big Data, and Big Data does not break with basic scientific principles. However, within the last decade Big Data has often been discussed as a new paradigm in empirical science in terms of data types, sources and epistemological implications. An often-cited instigator of the larger discussion about Big Data is Chris Anderson's short blog post for *Wired Magazine* in 2008, in which he announced, 'the end of theory'. The claim is that as data collections become very large and multifaceted the explanatory and predictive power of patterns extracted from the data will make all theoretically motivated models obsolete. While such a naïve claim is easily refuted in a number of ways, it does highlight what lies at the heart of the Big Data discussion, which is whether Big Data methods allow for entirely new ways of extracting knowledge (Schroeder, 2014). Whether Big Data constitutes an entirely new scientific paradigm or not lies outside the scope of this thesis, but the fact that the question is even asked suggests that at least some novel methodological phenomena have come about.

One of the most famous definitions of Big Data is that data has to have a high degree of *volume, velocity* and *variety*. This definition did not originate in the academic world but was adapted from an old report from 2001 by the consultancy company META Group and later promoted at a conference held by the company Gartner in 2012. It has become a commonly used definition and has later been adapted into a more rigorous framework by Kitchin (2014b), to which he also added five additional criteria: *Exhaustivity, Resolution, Indexicality, Relationality* and *Flexibility*. To start from the top, Big Data should be large in volume although this criterion can be difficult to use in practice since 'large' is highly context dependent (Lagoze, 2014). It implements high velocity being continuously accessible in near real-time, which is typical of data streams arising from mobile device sensors and social media APIs where data is constantly produced and pushed through digital channels. There is much variety such that every single data point, each observation, has many recorded features (e.g. measurements, timestamps, geo-location, categories, colour codes etc.). Data is also exhaustive, which in many ways can be considered a more precise definition of volume. Instead of insisting that data should have a large absolute volume, it should rather be exhaustive relative to the object of study. Thus, if your object of study is itself small, then your data volume can be small but still exhaustive meaning it contains every single relevant data point. This is what Mayer-Schoenberger & Cuckier (2013) calls 'N=all', which, in simple terms, signals a move away from the sampling procedures that have been emblematic of scientific studies in the 20th century. Instead of taking a data sample you simply look at the data in its entirety. Exhaustivity is then often linked with Kitchin's fifth and sixth criteria of resolution and indexicality where Big Data strives to have as many data points as possible, even if the object of study is small, and have every point be uniquely indexical. This automatically provides high resolution which allows researchers to study broad trends while at the same time having the opportunity to 'zoom in' on very specific subsections of the data (Bornakke & Due, 2018). In extension Big Data must have a high degree of relationality and flexibility, which implies that all data points should be easily connected to each other, or potentially to external data collections, and be flexible in the sense that a data collection is not dependent on having a fixed number of rows, but can be cleanly expanded or shrunk. As a final point it is worth mentioning that Kitchin does not claim that all criteria must be met in order for data to be Big Data. Instead Big Data is being used in situations where the data at hand naturally fit at least a number of the criteria, but not necessarily all of them (Kitchin, 2014, 6).

With those being the overall characteristics of Big Data, what then are the implications for the development of research methods? Before approaching this question, it is critical to mention the typical sources and enablers of Big Data. Without going into too much detail, the proliferation of Big Data in social science is largely due to a huge expansion and availability of online records of behaviour and sensor technologies[13] with the former being most relevant for this thesis (see Kitchin, 2014 for a detailed list). Data about what people search for, what they say, when they do it, to whom and with whom they do it and where they are when they do it can be sourced directly from online platforms without asking each single person to be part of a study. This of course poses some ethical questions that will be addressed at the end of this chapter. For now, the use of online records of behaviour introduces a significant shift in social science from *created data,* which consists of designing surveys and interviews, finding participants and getting responses, to *found data* (Jensen, 2013) or *exhaust data,* as it is sometimes referred to (Amen & Clark, 2018), where the data of interest are technically mere by-products or digital traces of people's behaviour.

This has important methodological implications for how data is used. First, since data is not created with a specific research purpose it is messier to deal with, which is also a consequence of the large volume and variety of the data. The notion of messy data is related to the unpredictable nature of data availability. The same kind of data might not contain the same variables if they come from different sources, but they still need to be combined. Working with such unpredictability is called *veracity* of data (Kitchin & McArdle, 2016). There is simply going to be more data than you need and thus you need to sift through it to some extent; and if it does happen that most or all of the data is needed, it might not be structured in a way that is appropriate for the research you are conducting. At the same time the opposite effect is also present, meaning that one aspect of the data might contain a lot more information than what you need while another contains less. This is often the case with social media and privacy settings where some data collections will have incomplete fields across a number of variables depending on the user's settings (Madsen, 2015). There is however a kind of trade-off between messiness and volume, especially if you are studying broader trends where a degree of messiness becomes acceptable once you have enough data points (Mayer-Schoenberg &

[13] Alex Pentland and Sensing DTU examples

Cuckier, 2013, 47). This means that researchers in most cases still have to wrangle, clean and manipulate data, as they did before Big Data, but the challenges have become very different. This leads to the second and maybe most significant implication for the actual methods being used with Big Data, namely *data driven methods*.

Data driven methods are best described in opposition to theory driven methods. An important point here is that this shift does not entail the so-called end-of-theory, which was mentioned earlier (Kitchin, 2014). Data driven methods for research purposes are almost always used in conjunction with some theoretical framework. The difference is that instead of proposing a theory and then collecting data explicitly to verify or falsify that theory using established methods, the researcher starts out with all available data and then proceeds to design methods specifically around the data in order to produce support or resistance towards a theoretical line (Ruppert, 2015). Data driven methods do not exempt one from having a rigorous research design. One should be careful not to propose a theory that is born only of data as it often leaves open the possibilities for spurious connections to occur (Calude & Longo, 2017). Another way of putting it is to say that data driven methods for research purposes, especially in social science, are not a purely technical endeavour, but a combination of social and technological features (Bowker et al., 2009, 18).

Data driven methods are different from the carefully constructed research designs of theory driven methods, but they are not simply a return to descriptive statistics either. Because Big Data is larger, more varied, faster and messier than traditionally collected data, it will often require one or more steps of pre-processing before it can be used to adequately study a social phenomenon. It is within these pre-processing steps that the actual 'method' of data driven methods can be found.

Data driven methods are still a somewhat novel concept and there are no definitions which are widely accepted at the time of writing, however Madsen (2015) has proposed a useful framework for understanding and categorizing the overall strategies used in designing data driven methods specifically for social science studies of online digital media. As shown in figure 4.0 these strategies can be divided into four categories along two axes such that the design of data driven methods conform to either *training* or *following* approaches and either *structured channelling* or *adaptive tracking*. Training and following strategies are born of a necessity for automation when dealing with data that are exhaustive and have high volume or velocity. The strategy of 'following' entails designing an algorithmic method that can extract interesting patterns from the data independently of whether the patterns at the outset have any social significance. In machine learning terminology, this is often referred to as *unsupervised machine learning* or *clustering* (Géron, 2017, 19). For research purposes this inevitably requires a human to interpret the patterns detected by the algorithm, which is where theoretical motivations and expert domain knowledge become important guiding principles for any meaningful results to be extracted from such 'naturally occurring' patterns. Training then corresponds to what is often called *supervised machine learning* (Géron, 2017, 17) where algorithms are designed specifically to recognize previously occurring patterns automatically such as whether messages have negative or positive sentiments.

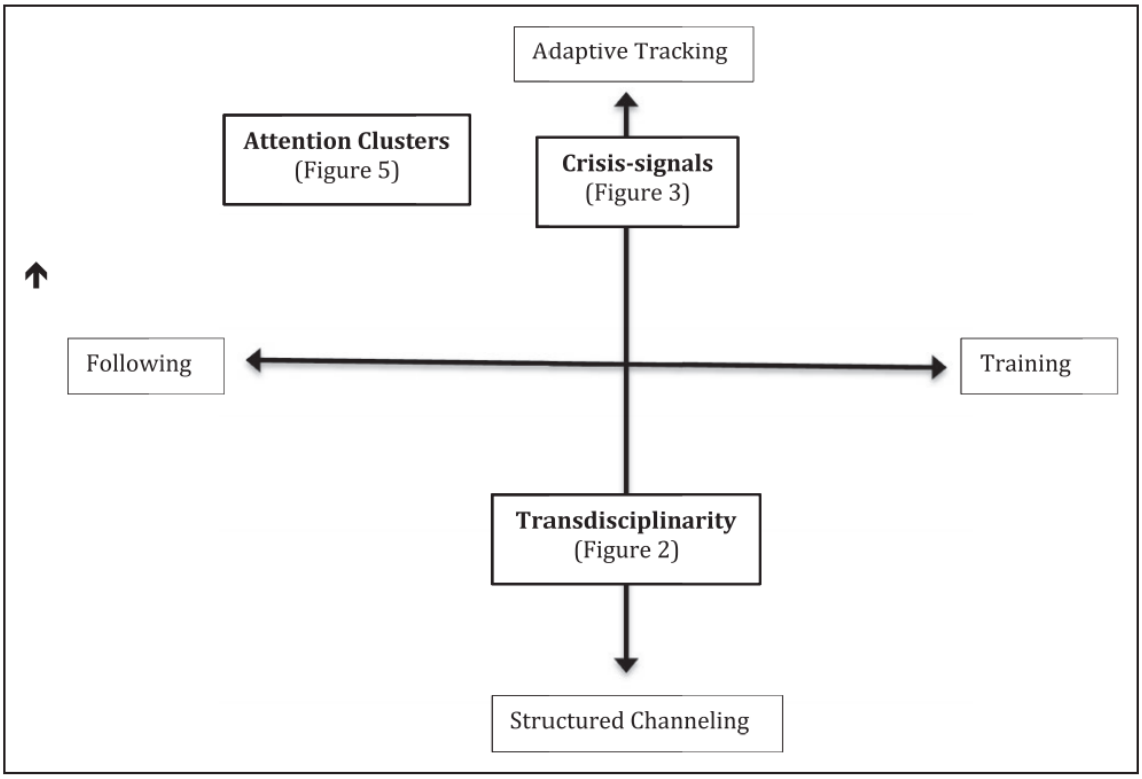

FIGURE 4.0 – DATA DRIVEN METHODS.

A two-dimensional space for locating data-driven methods in social science. (Madsen, 2015)

Structured channelling and adaptive tracking can be seen as a response to Big Data being very multifaceted, flexible and granular. The degree to which data driven methods apply either of the two depends on how much pre-processing, or rather how much adaptation of the data occurs. Structured channelling is when the data categories, as they have been determined by the source, are used more or less directly in the research design. As an example, Facebook has certain categories for different types of actions and interactions, such as posts, comments, replies, shares or emoji responses that have sub-categories of like, love, angry, sad, wow, haha. A structured channelling approach is using an interaction such as 'angry' as representative of a certain kind of social behaviour, whereas adaptive tracking seeks to build new categories out of the original data such as looking at angry/love ratios rather than just 'love' and 'angry' emoji responses in isolation.

Because the work with Big Data is relatively new in social science research most of the methodological literature is *descriptive* rather than *prescriptive*. At the same time there is an explosion of interdisciplinary research, not only because social scientists are seeking out ways to harness the benefits of Big Data, but also because scholars from fields such as biology, physics, computer science, statistics and engineering have sought to apply Big Data methods developed in their own field to social science research questions. As has been noted on multiple occasions by Freelon (e.g. 2014) a great deal of interdisciplinary research that study social phenomena falls short when it comes to interdisciplinarity. Social scientists are lacking in their knowledge of advanced statistics and technical skills needed to handle large amounts of data, while scholars from other fields have a tendency to oversimplify social behaviour to fit models used to study things such as bacteria, viruses, fluid dynamics. Part of the work in this thesis is to be mindful of this divide and seek to bridge it.

In order to address the novelty and lack of clear methodological tradition for Big Data, and computational methods more broadly, this section has sought to give an introduction to the evolution of the field as it has been described by some scholars over the last decade. The following sections will first present the research design and data collected for the empirical work in this thesis followed by the methodological limitations and ethical considerations.

Research Design

This section briefly outlines the main choices and considerations in discovering, collecting and preparing data for analysis. The chapters that follow will go into greater detail about each step of the way. The purpose of this thesis is to study public opinion formation in the context of political homophily and agreement/disagreement between citizens on social media *in general* and not in relation to a specific political event or community, though some narrowing down of the scope is necessary.

The main data for this project is behavioural data sourced from public Facebook pages in Denmark. A major limitation, which is due to both technical barriers and ethical concerns, is that only data from public pages is collected. The bulk of Facebook activity takes place in private groups and chats and many people rarely seek out public forums (Rossi, Schwartz & Mahnke, 2016). For this reason, it is important to reiterate the purpose of the study which is not to infer what people use Facebook for, but rather examine the potential for social media as a public space where political knowledge can be obtained, and new opinions formed. As such, not all people have to participate the same amount. One of the benefits of rational ignorance in the triaxial model is that people are at liberty to participate to the extent they please.

As a response to the necessity of dealing with Big Data produced by social media, the methodological framework *social analytics* has been proposed (Zeng et al., 2010). It is not a well-defined method, but an overall framework that has been developed for multiple use cases. The core idea is based on a data-driven methodology as it was described in the previous section. This is illustrated well in the basic model laid out by Fan & Gordon (2014) that specifies the direction of the process as *capture -> understand -> present*, which clearly indicates that one starts with the data rather than the theory. The research design in this thesis is based on the model for social media analytics in political contexts proposed by Stieglitz & Dang-Xuan (2013) and further refined by Stieglitz, Dang-Xuan, Bruns, Neuberger (2014) and Stieglitz, Mirbabaie, Ross & Neuberger (2018), which is illustrated in figure 4.1 The framework illustrates the linear process of collecting, preparing and analysing data sourced from social media.

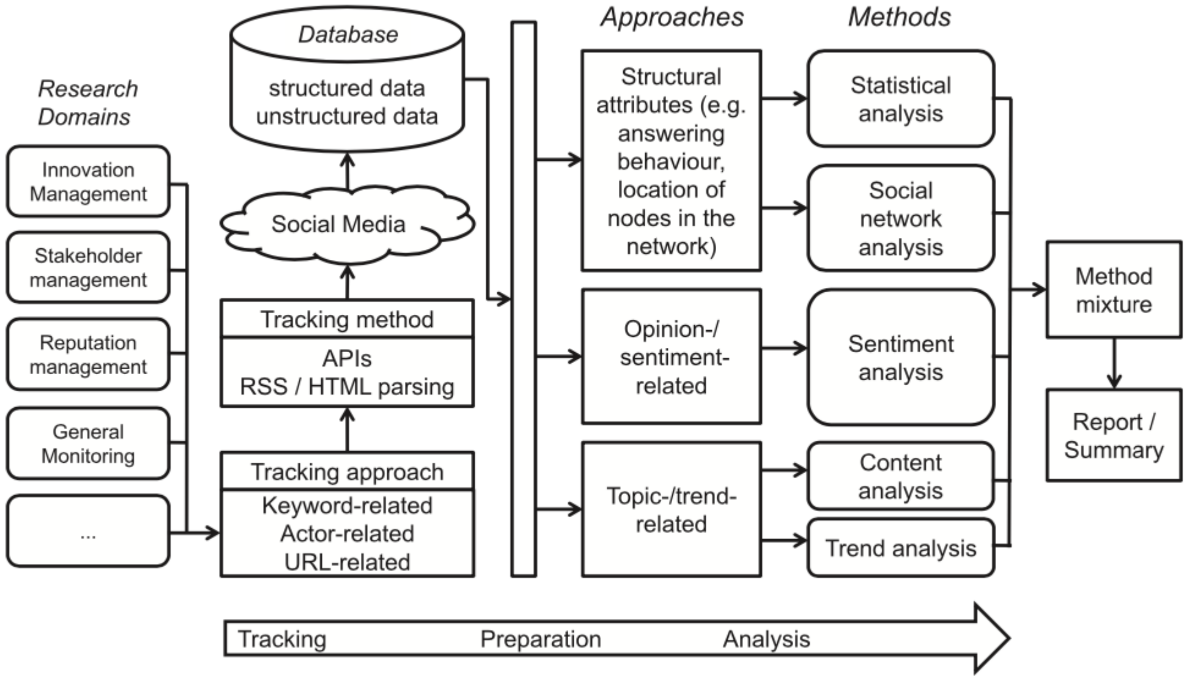

FIGURE 4.1 – SOCIAL ANALYTICS FRAMEWORK.

In this thesis the tracking source is Facebook, specifically public pages, and the tracking method is the HTTP version of the Facebook Graph API 2.x, which is the most common way of collecting data from Facebook (Sebei, Taieb & Aouicha, 2018). The method allows researchers to extract all behavioural data from public pages including who is posting, reacting and commenting, when it happens, on which pages and in response to what information. Data of interest for this study includes all instances of public opinion formation in the general public potentially related to politics. Since there is no API end-point called "the general public" and because the Facebook API does not allow for keyword or hashtag searches, an actor related tracking approach is necessary. This entails identifying all public actors be it a single person (i.e. politician) or an organisation that have the potential to become spaces for political discussion. It is impossible to even come close to identifying all public pages that are potentially related to political opinion formation, but an effort is made to make data as exhaustive as possible by collecting from all pages that represent politicians, political parties, media organisations, publishers, unions, local communities, NGOs, charities, public institutions and interest groups. This will provide a fairly exhaustive cross-section of all public discussion and interaction that is most likely to have political relevance in a Danish context. Many pages have a clear political frame such as those belonging to political parties, publishers focusing on political news, labour unions or pages dedicated to political movements. However, following the idea presented in the previous chapter that politically relevant discussions can arise in spaces that are not overtly political, other pages are also included such as gossip magazine, local sports clubs, charities and hobby groups. The pages are supposed to represent a fairly broad cross-section of society, but for practical reasons the selection is still tilted in favour of pages where political talk is more likely to occur. Initially many pages representing the music, film and entertainment industries were included, but then discarded as the occurrences of politically relevant discussions seemed extremely rare compared to how much data needed to be collected. Details on the selection of these pages will be covered in the following section.

In order to consider public opinion in relation to multiple contexts, all three analytic approaches illustrated in figure 4.1 are applied: 1) Network attributes, 2) sentiment related and 3) topic related. The purpose of the first is to determine the political stance of users based on which actors they interact with. The second approach has the goal of leveraging information about how users engage in discussion by determining the sentiment and harshness of language in their comments. The third approach provides further insight into the content of the discussion by analysing the different topics that both posts and comments touch upon. In the 'method mixture' step of the research design all three approaches are combined into a final analysis that considers the overlap between network, sentiment and content. The three approaches entail a great deal of data preparation, an element that is often underdeveloped in the social media analytics literature. Data preparation is closely tied to the analysis and can be described as "…shaping the data into a format that allows it to be analysed for the intended purpose." (Stieglitz, Mirbabaie, Ross & Neuberger, 2018, 160). However, the importance of this process is often downplayed by simply equating it with procedures such as data cleaning, data refining or data reduction (e.g. Sebei, Taieb & Aouicha, 2018). It gives the impression that data preparation is mostly a technical step. On a practical level the data preparation process involves many choices by the researcher that become closely tied to the types of results and potential interpretations that can be made in the end (boyd & Crawford, 2012). The specifics regarding each of the three approaches are respectively covered in chapter 5, 6 and 7. The final analysis presented in chapter 8.

A secondary aspect involves the use of two surveys[14] with the purpose of asking participants about their political opinions and voting intention and further linking each respondent to her or his Facebook profile. The survey responses are used to create and test a classification algorithm that can then predict the political affiliation of all Facebook users in the Danish dataset. This can greatly increase the strength and reliability of analysis done at the individual level and create a stronger connection between offline and online behaviour such that both can be assumed to mutually reflect each other (Wells & Thorson, 2017).

Data Selection and Collection

Facebook

As mentioned in the previous section, data from Facebook is the primary data source for the project. The goal is to obtain behavioural data that is representative of how political interactions plays out in the general public on Facebook pages, which entails seeking a selection of pages that is as exhaustive as possible. The approach is to identify all public Facebook pages where politically relevant interaction is likely to take place. This is done in five parts. The first consists of all Danish politicians with a Facebook page who was in parliament between 2010 and 2018 as well as all who ran for parliament in the election of 2015. The second is a selection of the most influential media producers and publishers and the third consists of public organizations such as the National Taxation and Tariffs office as well as interests groups such as charities and NGOs. The fourth part contains the public Facebook pages of all workers' unions, which is a major source of influence in Danish political life. The fifth and last part is a selection of all pages that can be directly attributed to local activities within specific sub-regions of the country known as *communes,* which can be referred to as local community pages. The pages for part one and four includes all known actors as they are listed on publicly available lists while part two and three were identified by looking up their respective categories on

[14] The surveys were carried out for the purpose of publishing a journal paper. They have been repurposed in this thesis.

socialbakers.com[15] and getting all pages listed. The pages for part five are all those that either have the name of the commune or a major town within the commune in their page title or are registered as part of that commune, which is a feature provided by Facebook.

The data collected for all five parts captures the period between January 2014 and February 2018. The total breakdown of data for each part is illustrated in Appendix 4.0-SI. The part of the data that consist of all political pages is an exception and captures all activity between January 2010 and February 2018, however the main focus in this thesis is on the period starting in 2014.

The data is queried using the Facebook Graph API through an HTTP protocol. The program to handle the collection process was written specifically for this project in pure Python[16]. The collection program uses a MySQL database to store the data, although, according to the Big Data literature, SQL-based DBMSs are not preferred for Big Data (Huang et al., 2015; Anderson et al., 2015). MySQL was chosen as the database management system due to the author having much more experience with said system. It was estimated to be sufficient for the storing and handling of the data for the project despite not being a preferred Big Data technology. While data from a single Facebook page is theoretically infinitely expandable with no upper limit, the population of a country is a fixed size and thus it is possible to make a broad, but reliable estimate for how much data one can be expected to store.

The data available for collection at the time (2016 - 2018) is as follows: For each identified page it is possible to collect all posts made on that page. For each post on the page 0 – n reactions can be made where each reaction can be any of six emoji style types: Like, Angry, Sad, Wow, Haha and Love. Furthermore, every post can have 0 – n comments to which each comment can have 0 – n reactions as well as 0 – N replies, which is a comment to a comment. Finally, each reply can have 0 – n reactions. At the comment and reply level only positive reactions i.e. Like, Love emojis were collected. The different types of data available for each of these types of interactions is shown in Appendix 4.1-SI.

The data to be collected does indeed qualify as Big Data on multiple counts. The full data collection takes up more than a billion rows with a variety of hierarchies, data types and data formats to consider. It is high resolution and uniquely indexical such that a single

[15] Consulted in December 2017.
[16] A popular and flexible programming language that is used both for general tasks as well as data analysis.

reaction made to a single Facebook post can be identified by unique user id, type and date, and there are no upper or lower limits for how much data can be attributed to a single Facebook page, post or comment.

Instead of describing all the raw data collected for each interaction it is more useful to explain the information that can be extracted. The analysis in this thesis will take advantage of the following pieces of information that can be extracted from the collected data: The date and time of a single interaction, who is responsible for the interaction, with whom the interaction occurred, on which page it happened, the type of interaction, the text of posts and comments and the first name of the person who initiated the interaction (unless it was a page). With just these fairly few pieces of information it is possible, by properly preparing the data, to complete the entire analysis for the thesis and approach an answer to the main research questions. Making real use of the data is of course not an easy task as the amount for just the Danish dataset comes to almost one billion rows. As mentioned earlier, preparing the data and extracting the necessary information require a series of separate analyses, which are covered in chapter 5, 6 and 7.

Surveys

Two surveys have been requisitioned for this thesis. Both serve the purpose of securing an offline "ground truth" that link people's social media behaviour to their political preferences. The first, which is the main one, is a stratified random sample of the Danish population. The stratified random sampling technique is used in order to most accurately reflect the actual population across a series of key demographic variables such as sex, education, place of residence and income (Deacon, 2007, 20). A special feature of the survey is that respondents are asked to log on to their Facebook and thereby connect their answers to their Facebook profile. Denmark has a very high penetration of Facebook use (Statistics Denmark, 2016) so you can reliably assume that many respondents will have their own Facebook profile. However, there are two additional factors that might increase the dropout rate: 1) not all respondents are willing to hand over their Facebook data; 2) not all respondents are active on public Facebook pages. As part of taking the survey it is explicitly explained that no private data will be collected from the respondents' profiles but having to officially create a link between their answers and their online profiles is enough to make people sceptical and opt out. After dropout the final sample consists of a slightly more skewed, but still sufficient representation of the national population, though the sample size is severely reduced. This is explained more in detail in the next chapter.

The purpose of the first survey is to link participants to their *public* behaviour and thus no access to their private accounts was obtained. Only a uniquely identifiable ID was provided, which would allow their actions on public pages to be linked to their responses. Importantly, the ID cannot be used to do a reverse lookup on Facebook, which means that the whole process can be carried out without the researcher ever knowing who any of the respondents are. The survey was carried out by the Scandinavian based company Userneeds and only the anonymized data was passed on[17]. The main purpose of the survey is to develop a method that can reliably predict the political affiliation of a single Facebook user, which is covered in Chapter 5.

A second survey was done at a later stage by the Danish company Analyse & Tal with the purpose of making the predictions about political affiliations better as well as expanding the predictive algorithm to a few other areas such as place of residence. The procedure was similar to that of the first survey. The sampling technique used however was convenience sampling (Deacon, 2007, 56), which produces heavily skewed results with respect to the national population. For this reason, it was only used together with the first survey in chapter 8 where the purpose is more exploratory.

Limitations Imposed by Data and Methods

This section will cover the overall limitations that are inherently imposed by the data selection and methodological framework. Limitations that are very specific to certain parts of the data preparation are contained in their respective chapters.

The study is based on a Big Data and data-driven methodology, which raises some immediate concerns. One that is worth mentioning right off the bat is that N is never equal to all and social media activity does not represent people as such (boyd & Crawford, 2011, 532). This observation criticizes claims related to volume and exhaustiveness in Big Data,

[17] The survey was done purely for research purposes with no commercial incentive.

particularly the end-of-theory argument claiming that having more data is better than having sound theories. While the setup for this project has allowed the collection of all Facebook posts by all politicians over the last 10 years in Denmark rather than just a sample, assuming that this collection represents all political discourse or something similar would be very wrong. Some politicians do not have Facebook pages and, as mentioned in the last section, not all people are active on public pages. In fact, a great deal of people who use social media are 'lurkers' meaning they do not actively participate, but only observe what other users are doing (Kohring & Zimmerman, 2018). Since only interactions that consist of reactions, posts, comments and tags can be collected with the Facebook API, all lurking activities are excluded. The data used in this study has been collected largely because it is *collectable*, while that which is not collectable is ignored by default. This is what Axel Bruns (2013) calls simply a 'data bias', but it can also be referred to as 'omitted voices' (Hargittai, 2020). Not everyone gets to be part of the so-called exhaustive dataset. This bias does not invalidate the research design, but it is important for considering which conclusions can potentially be drawn from it. This thesis will assume to represent only people who are interested in engaging in public spaces on social media rather than the entire national population or even all people who use social media.

Similarly to problems with data biases, the urge to collect a lot of data can result in a loss of the context surrounding the activity that the data represents. Big Data without context loses its meaning (boyd & Crawford, 2012). This project has sacrificed qualitative knowledge about how people interact differently in various forums on social media in the pursuit of volume and exhaustiveness. Data has been collected from thousands of public Facebook pages, many of them without insight into why they were created, what the motivations for users to engage with them are or if the space has diverged from its original purpose of creation. The focus of this thesis is on broad trends, which makes it possible to ignore some of details pertaining to behaviour on individual pages, however it will still be important to remain mindful of details that have potentially been overlooked, especially when observations are only weak trends.

An important aspect of Big Data methods, especially with social media data, is the lack of control in respect to access, data conventions and transparency. Engaging with Big Data methods entails working within zones of limited control (Lagoze, 2014). This lack of control can be divided into two significant areas, which Madsen (2015) refer to as *blue* and *red data dynamics*.

Blue data dynamics have to do with the control over data structures, formats and organisation. Social media platforms work with different concepts of how people communicate, e.g. a retweet on Twitter is embedded in a completely different data structure than a share on Facebook, which has implications for how the data is queried. Platforms might also change, expand or reduce the data available without the researcher's knowledge. A good example is when Facebook added a range of emoji reactions for users to choose among over the classic like button when interacting with a post or comment. This has consequences for the technical setup that has to be changed in order to capture the added feature, but it also has conceptual consequences for researchers who are trying to understand behaviour from longitudinal perspectives. Does a like on Facebook mean something different after the user can choose between other reactions than it did back when users could only choose between liking and not liking?

Red data dynamics has to do with access and transparency. The administrators of a certain social media platform have complete autonomy (within legal boundaries) when it comes to deciding what data to make available at which times and what to keep hidden. These decisions might not be well-thought out and they are not intended to help people doing research. A good example is the Facebook Graph API 2.x, which is used for this project, where it is possible to query the user ID for people who react to or comment on a public post, but not users who share that post. Furthermore, the lack of transparency might be an even greater cause for concern than access. When whole sections of the data, such as user IDs for people who share public posts, are not available, it is at least obvious that some parts of the data are missing. But when there is no transparency in regard to what comments have been removed or which pages are not allowed on the platform in the first place, researchers do not know the full history behind the data sample that they end up with. This adds another layer of uncertainty that should be ackknowlegded when interpreting the data.

Ethics

At the time of writing social media and data obtained from digital platforms is a controversial topic, not just for researchers, law makers and private corporations, but for the general public (e.g. Naughton, 2019). This most often revolves around lack of privacy rights and lack of tools to control and mange one's own digital trace data as well as a general lack of trust in those actors with privileged access to all the data such as the big tech companies that currently host the platforms (Isaac, Kang & Popper, 2019), but also clandestine organizations (Lyon, 2014) and the political elite (Fuchs, 2016.).

For social science researchers the main issue is the lack of procedures for obtaining consent from people whose data is potentially going to become part of a study. Prior to the era of social media the process of obtaining consent was inscribed into the process of seeking out participants for either surveys, interviews or observational studies. Social media and the APIs that allow researchers to access the data stream directly inevitably circumvent both the necessity and incentive to obtain consent from individuals. The problematic circumstance can be tied to some of the defining characteristics of Big Data such as the earlier mentioned concept of *exhaust data* that is the repurposing of data that was not created for the purpose of research.

Users do agree to the terms of services that solve the legal issues around letting third party actors have access to parts of the data, though that does not necessarily make it ethical (Ixchel & Zimmerman, 2011). Some studies such as the famous "emotional contagion study" in which researchers with privileged access manipulated the content feeds of Facebook users to study whether it had an impact on the emotional states of the users, have received a lot of criticism for disregarding the ethics of using social media data (Panger, 2016).

One prevalent problem comes from the fact that there is a lack of specific guidelines for how to handle social media data in the academic world. The Human Ethics Boards approached by the author for this study, which include the University of Canterbury Ethics Board and the Danish Datastyrelsen did not have a specific procedure for obtaining approval to use data that was available through public APIs. The methods used in this thesis have, to the best ability of the author, abided by the ethics guidelines developed by the Association of Internet Research[18].

The biggest concern has been to ensure that no private content was ever accessed and that no data could be directly traced to a unique individual. All data come only from pages that are labelled as public and user activity was not cross referenced with other data sources except for the two surveys. Again, it is important to recognize that just because a space is labelled public on Facebook, consent to be part of a study cannot be assumed on the part of an individual who is active in such a space. All IDs in the data collection used to identify participants are completely anonymized and cannot be traced back to an individual. As mentioned earlier the process of connecting the survey to the Facebook data was set up in a way which ensured that the author was never in contact with any de-anonymized personal information. The only remaining problem is that the full text of individual comments made on these pages were collected. Many such comments are unique enough such that if one was to go to the public Facebook page and manually look for the comment it would be possible to at least find out which user made the comment. How much information that would be available on the user then depends on the privacy settings chosen by that user. This problem can only be mitigated by keeping the raw data secure and private. However, as a way to limit the capabilities of the analyst, the code developed for parsing the data hides all comments in the final data set and show only aggregated results for posts made by public pages.

The reason for undertaking this research is that by using and studying the data it is possible to expand the public knowledge about how online behavioural data can be used. From a consequentialist standpoint the assessment is that the risk of harm to individuals is minimal compared to the potential gain for the public.

The ethical considerations become especially relevant in this project, specifically because the main data source is very similar to the one used by the infamous Cambrigde Analytica, which caused a major scandal in 2017 when the world learned that they had been using users' digital traces from Facebook without their knowledge or consent in order to make targeted political ad campaigns. Contrary to the research conducted at Cambridge Analytica, the vision for this project is to make the ability to use digital trace data as a

[18] https://aoir.org/ire30/

form of public communication rather for analyses to be carried out behind closed doors. This is to narrow the gap between what corporations and professional organizations can do with data and the capabilities of ordinary people, increasing the data agency of the public (Kennedy, Poell & Van Dijck, 2015). There is a long way from leveraging digital trace data from the privileged position of a university student to the same being possible by the general public, however presenting the methods openly can be regarded as a step in the right direction. The hope is for powerful analytical tools to become increasingly public and function as part of vigorous democratic debate rather than instruments of manipulation.

Chapter 5. Predicting Voter Intention in Multiparty Systems

The purpose of the present chapter is to describe the first part of the data preparation which is to ascertain the political stance of all Facebook users in the data collection. This part of the data preparation seeks to leverage the network attributes of digital footprints left behind by users on social media. Essentially social network analysis is about relations (edges) between people (nodes) (Tsetovat & Kouznetsov, 2011, 2). Edges shared by nodes and nodes that intersect with edges can tell stories about the latent relations between people. The focus in this chapter is on user activity on various pages in the Danish public with the purpose of predicting their political stance. Providing empirical evidence for the feasibility of predicting political preference from behaviour on public pages is necessary in order to further explore the distribution of political homophily and polarization.

Applying network analysis becomes very complex and computationally expensive at scale. Since the focus is not on exploring complex networks, but making straight predictions about users' political stance, only relations in the first degree will be considered for analysis. More complex relationships will be explored later in the final analysis, but for the purpose of prediction only the pages that users visit themselves will be considered. If a user goes to a public page and likes a post it does not matter which pages other users who like that post also go to. This is not to say that such activity is not relevant, but in order to make calculations that are realistic with the computing power available, only relationships between users and pages are included, not the myriad of implicit relationships between users on public pages. More specifically, this entails calculating only the in-degree between users and pages (i.e. how many times a user has interacted with posts on a given page) and then treating this metric as a multivariate regression problem rather than a graph problem. Network attributes will be compared with responses from a nationally representative survey in order to test how well they can be used to predict the voting intention of a single user.[19]

From Sociodemographic Attributes to social Media Traces

The representative opinion survey has long been the pinnacle of empirical research in political science (Campbell, 1960; Verba, 1987). The recent immense growth in digital platforms has provided researchers with the possibility of studying human behaviour on a whole new scale from traces left behind by our digital interactions (Dalton, 2016). No longer being limited to surveys with a couple of thousand respondents, political studies covering millions of people have emerged within the field of computational social science, generating important new knowledge about our digital and analogue lives.

Within the subfield of election forecasting, scholars have shown the potential for predicting election outcomes based on digital data from a diverse range of platforms including YouTube (Franch, 2010) Google (Mavragani, 2016) , Twitter (Ceron, Curini & Iacus, 2016; Jungherr, 2015), Facebook (Giglietto, 2012; Barclay et al., 2015), and even Wikipedia (Yasseri & Bright, 2016). Studies based on the big social media platforms that is, Facebook and Twitter have largely been the most successful with prediction rates that, in terms of accuracy and scale, have often outperformed traditional polling (e.g. Franch, 2010, see Ceron, Curini & Iacus, 2015 for a review). While this emerging field has mainly focused on predicting aggregated electoral results (Makazhanov, 2014), a smaller group of studies has focused on the challenge of predicting individual political orientation (e.g. Kosinski, Stillwell & Graepel, 2013; Adali & Golbeck, 2014; Youyou, Kosinski, Stillwell, 2015; Volkova et al., 2015; Zhitomirsky-Geffet, Koppel & Uzan, 2016). Notably, Ceron et al. (2015) were able to reach very high accuracies in their political profiling using only Twitter data. Zhitomirsky-Geffet, Koppel & Uzan (2016) displayed how political orientation can be determined by comparing individuals' writing style with the writings

[19] Most of the work done in this chapter was has been previously published as a journal paper for which the Thesis author was also lead author. Co-authors include Magnus Skovrind Pedersen, Michael Jensen, Emil Dahl-Nielsen, Thomas Albrechtsen and Tobias Bornakke. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0184562

on politicians' public Facebook profiles. While many of these studies attain high prediction accuracies, this accuracy is often reached by limiting the study to the most active users (Volkova et al., 2015). Furthermore, few studies validate their results against offline data such as surveys (Thomson & Wells, 2017). These limitations have, however, been tackled in the works of Kosinski and colleagues (2013; 2015) who have shown how personality and political attitudes can be predicted with great accuracy based solely on Facebook likes. Applying machine learning algorithms to search for patterns in hundreds of diverse Facebook likes, these already famous experiments have thus disclosed how people's preferences for Hallo Kitty and Harley Davidson can reveal details about their personality and political attitudes — often with better precision than their friends or family.

Thus far, the majority of studies predicting individual voting behaviour based on digital traces have focused on two-party systems or applied a left/right-wing scale, thereby avoiding the more challenging task of making all-inclusive predictions in multiparty settings. In the present study, this gap is filled by considering how individual party choice in a multiparty system is linked to liking posts made by political actors on Facebook. The predictions are based on likes on posts on public pages of Danish parties and politicians collected between January 2015 and 2017 through the Facebook Graph API. Through machine learning–based prediction models, 'political likes', consisting of likes on posts created by politicians and parties, are evaluated for their ability to predict present-day voter intention in a multiparty system for a subsample of surveyed respondents.

Data Recap

Predictions for the models developed in this chapter are based on positive reactions entered in posts by Danish parties and politicians on their public pages between 2014 and 2018. Emoji reactions are generic mechanisms used by Facebook users to express their sentiment about content, which has already shown to be a good proxy for predicting both electoral results and personal traits (as mentioned in the previous section), making it an immediate choice for exploring the possibility for predicting political orientation. Only respondents who were able, and willing to share their public Facebook ID (N = 1216) are included in this analysis. Additionally, it is limited to respondents who had liked political actors during the period and would vote for any of the nine parties in parliament during that time (N = 659). Dropout is not unexpected, especially considering that it is very unlikely that all Danish people are active on public Facebook people. The country has a population of around 5.5 million, but the number of distinct users in the Facebook data collection is 1.3 million. The final sample is slightly smaller (~23%) than one would expect given that the data collection contains 1.3 million users. Most of the dropout is likely due to privacy concerns (Appendix 5.0-SI). As a result of this dropout, representativeness of the data sample becomes slightly distorted (see non-response analysis in Appendix 5.1-SI). However, for the most part, the distortion simply reproduces Facebook's already skewed user groups with the only large bias being an underrepresentation of older users; a skew that was recently shown to have limited effect on how often a person would like political actors (Kalsnes and Larsson, 2017). The data process is illustrated in Figure 5.0.

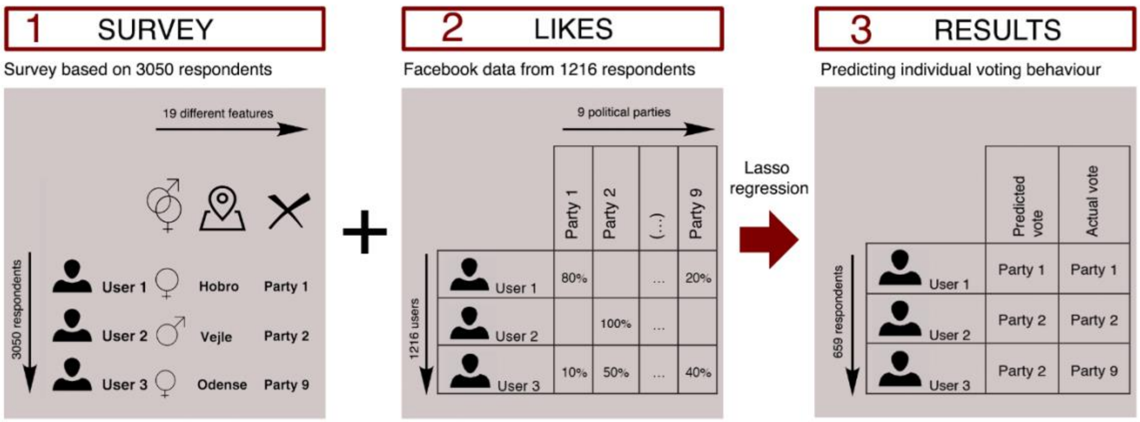

FIGURE 5.0 – THE DATA PROCESS IN THREE PARTS

(1) A representative survey was completed by 3050 randomly selected people living in Denmark, providing information on standard sociodemographic qualities, political values, and present-day voter intention toward parties eligible in the general election. As shown in Appendix 5.1-SI, the sample is somewhat demographically representative of the country's entire population. Respondents were subsequently asked to log in with their Facebook account, and if willing to accept the same, respondents' public Facebook ID was stored. (2) Post-likes were independently collected from all public profiles of Danish parties and politicians on Facebook. (3) After completion of steps 1 and 2, each respondent linked to the collected Facebook data and applied a LASSO-based multinomial logistic regression model to predict voter intention based on Facebook data.

The purpose is to predict the voting intention that was stated a given respondent in the survey. The primary method employed is multinomial logistic regression models that use machine learning techniques to optimize a function that models the relationship between network attributes and voting intention. Several models are constructed, including a baseline model that contains only responses from the survey (i.e. sociodemographic attributes, political attitudes, and opinions on political issues (see survey features in Table in Appendix 5.1-SI)).

Moving on from the baseline model, a selection of multinomial logistic regression models is gradually compared, all predicting which party a person would vote for but modelled on different selections of Facebook data as well as combinations of Facebook and survey data. Using L1 regularization (LASSO) (Tibshirani, 1996), only features that contribute significantly to the overall prediction are included in the models. In each model an L1 penalty was selected using 10-fold cross validation with a train/test split of 85/15 to avoid overfitting and account for variance in the prediction accuracy.

Feature Engineering and Feature Weighting

The process of feature engineering addresses the selection of the most appropriate features or set of features for any given model (Géron, 2017, 25-26). This can be accomplished by testing many different models or by testing the potential contribution value of individual features prior to modelling. In machine learning based on gradient descend, as in this case, weights for all features are constantly adjusted, raised or lowered, until the optimum for the log likelihood function is achieved. One special trait of L1 regularization is that noisy features, meaning features that only contribute to the predictive power of the model if they are unreasonably high or low, are given a weight of 0.0, thus effectively removing them from the model. This does obscure the relevance of features since all models are evaluated based on the features used in the inputs and not the ones selected by the algorithm in the final model. This though is fairly typical for models that aim to reach the highest predictive power rather than exploring individual features. As an example, chapter 8 will employ different kinds of statistical models, some that better allow for exploring the strength and relevance of individual features.

Model Performance

The results depict how different uses of "political likes" are able to predict which of the nine parties in the Danish parliament a given person would vote for. The significance of the results is held against a null hypothesis that denotes no relationship between present-day voter intention and explanatory variables (H_0: P = 1/9). The results are found in Figure 5.1. Detailed description of relevant evaluation metrics can be found in Appendix 5.2-SI.

	Baseline model***	Model I***	Model II***	Model III***	Model IV***
Description	Sociodemographic political values	Single latest political like*	All political likes	Model II + Baseline model	All political likes with min likes 7
Sample size	659	659	659	659	468
L1-penalty	10.0	0.0	0.0	3.0	0.0
Incl./excl. coefficients	101/668	90/90	90/90	300/680	90/90
±95% Confidence interval†	0.035	0.038	0.037	0.037	0.042
Precision	0.461	0.420	0.652	0.567	0.755
Recall	0.302	0.449	0.577	0.591	0.612
Accuracy	**0.358**	**0.439**	**0.609**	**0.620**	**0.708**
Left/right accuracy	0.803	0.813	0.908	0.933	0.96
AUC	**0.760**	**0.762**	**0.832**	**0.878**	**0.917**
Left/right AUC	0.819	0.801	0.912	0.939	0.990

*** = p < 0,00

* Latest political like refers to the like that a given person entered at the point in time closest to where she filled out the questionnaire.
† The confidence interval is calculated for the cross-validation error.

FIGURE 5.1 - MULTINOMIAL LOGISTIC REGRESSION MODELS PREDICTING PRESENT-DAY VOTING INTENTION

Establishing a Baseline From Sociodemographics, Political Values, and Opinions

The analysis is initiated by establishing a baseline model based on sociodemographic variables, political values, and opinions toward current issues collected through survey questions. The questions were selected to mirror the most typical variables for explaining voter alignment within the discipline of political science (Stubager, Hansen & Andersen, 2011). The baseline model (model 0) includes 19 different features. Note however, that several coefficients are neutralized by L1 regularization, which is implemented in LASSO regression to prevent model overfitting. The optimal model makes predictions with 35.8% accuracy (confidence interval [CI] of 2.9%) including 101 out of 668 coefficients. This echoes the accuracies of similar survey studies within political science, on average reaching an accuracy of approximately 35% [e.g., 20–22]. For comparison reasons, model accuracy is tested on predictions for present-day voting intention on a right versus left scale. Not surprisingly the accuracy is much higher when using this binary classification (80.3% accuracy).

The Power of a Single Political Like

With an established baseline model, attention turns toward the collected Facebook data. As an initial experiment, a model that uses just a single feature, the latest like that the respondent has entered to a post by a party or politician, is created. This very simple setup (model 1) is more accurate and, on average, marginally better than our baseline model. With an accuracy of 43.9% (CI ±3.8%) and a right/left accuracy of 81.3%, model 1 indicates that a person's single latest political post-like tends to say more about party choice than a prediction model trained on a sample with 19 different features on each person, including questions on core political values.

Raising Accuracy by Including Individuals' Entire Political-like History

In this part all political likes for each person collected during the two-year period (model 2) are included. The features in this model consist of the number of posts that a person has liked for each of the nine parties in parliament. For example, if a respondent has liked a post made by a party or a politician from that party on their public Facebook page, then that counts as one like to that party for that respondent. To compare respondents who are extremely active on public pages with those who are less active, all values are normalized across each respondent's likes toward each of the nine parties. Thus, all values are on a scale 0-1 representing the proportion of likes that a single respondent has toward a single party. Applying these features, it is possible to predict which party a person would vote for with an accuracy of 60.9% (CI ± 3.7%). This result is notably better than both the baseline model and model 1. Interestingly, the best L1 penalty in model 2 was 0.0, meaning that excluding coefficients would not increase the cross-validated accuracy. With a right/left average accuracy climbing to 90.1%, the model suggests political likes as an efficient predictor for voter intention.

Combining Survey and Political Likes only Minutely Increases Prediction Rate

The next model considers the possibility of a positive complementary effect by combining the best of two worlds. Features from the baseline model are added to model 2 in order to explore whether the survey questions encapsulate other dimensions than the political likes: Do the two approaches overlap or complement each other? The new model, model 3, hereby includes all the sociodemographic background information, core political values from the baseline model, and the entire political-like history from model 2. The prediction accuracy is now 62.0% with (CI ± 3.7%). This is higher than model 2, but still within the margin of error. The increase in area under the (receiver operating characteristic, or ROC) curve (AUC) and in right/left accuracy suggests that model 3 is still only slightly better than model 2.

The sample size in model 3 is lower than the number of coefficients, which is one probable explanation for why the added data does not deliver a significant increase in accuracy. Even though L1 regularization filters out most of the unnecessary noise, it is conceivable that the regression algorithm would perform much better with this selection of features if the sample size could be increased.

Optimizing Political-likes Prediction Rates with Minimum-like Criteria

The previous models propose political post-likes as the single strongest variable for predicting individual party choice. It is therefore reasonable to consider whether it is possible to further optimize the use of this variable. Since values for number of posts liked across each of the nine parties for each respondent are normalized, the models might make overconfident predictions based on respondents who have only liked a single post. Similarly, a person for whom 90% of likes go to the same party should yield better predictions than a person whose likes have been evenly distributed across several parties. This part will explore the relationship between these two criteria, namely (1) *minimum likes* which entails excluding respondents with less total likes than the threshold, and (2) *party like cap* which entails excluding respondents with a lower percentage of likes directed toward a single party than the threshold. The results can be seen in Figure 5.2, and Table 5.0 provides the values corresponding to the figure. Figure 5.2 shows how the accuracy increases with both min likes and party like cap indicating that respondents with many likes distributed to one or few parties yield the most accurate predictions. With, for example, min likes = 7 and party like cap = 0.8, prediction accuracy goes above 90%; however, sample size is down to 153, which also considerably increases the error rate (see Table 5.0).

Party-like cap	0.0	0.5	0.7	0.8	0.9
Sample size	468	328	197	153	97
95% Confidence interval (CI)	0.046	0.05	0.058	0.059	0.062
Accuracy	0.64	0.777	0.861	0.912	0.93

Table 5.0 – Party Like Caps and Minimum Like Criteria.

Prediction rates and sample sizes at different party-like caps with min likes = 7 ($p < 0.001$)

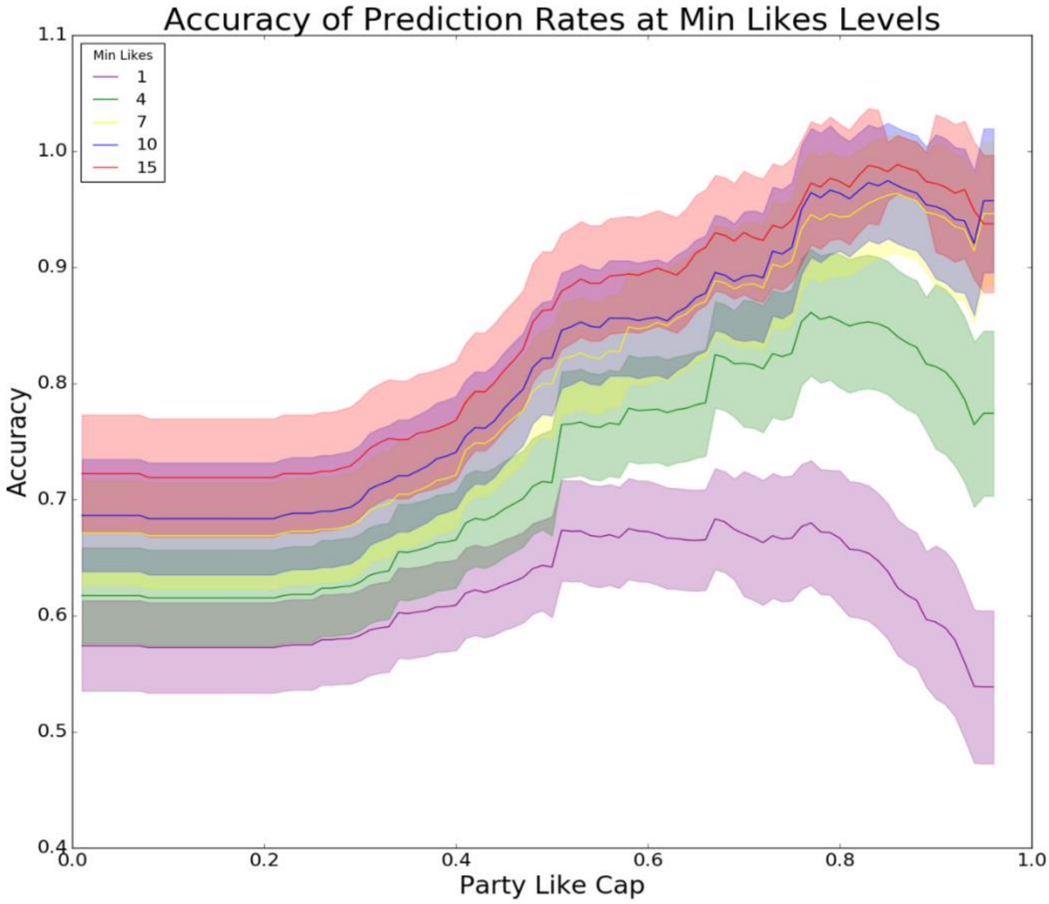

Figure 5.2 – Accuracy at Minimum Like Levels.

The x-axis shows party-like cap (PLC), which denotes how many likes at least go toward only a single party. At PLC = 0.8, only users who have at least 80% likes toward a single party are included. The y-axis shows the percentage of users who are accurately labelled. Each coloured line shows accuracy for samples where all respondents have a minimum of total likes. Because the two criteria, party-like cap and minimum likes, involve filtering out respondents and thus effectively cutting down the sample size, it is unfeasible to rely on the training of machine learning algorithms for classification. Consequently, a simple algorithm that derives predictions based on the party a respondent has liked the most at different intersections of the two criteria is available.

Thresholding Total Likes Greatly Increases Accuracy

Most importantly, Figure 5.2 shows that overall prediction rates, when thresholding individuals on their total likes, begin to converge significantly with a total minimum of 7 political likes. Setting the minimum likes criterion higher than 7 results in only a little gain in total accuracy, but considerably reduces sample size. A threshold of minimum 7 political likes is taken as the best choice for a near optimal prediction rate.

Based on the optimization exploration, we deploy a fourth and final model that has the same features as model 2, but only includes respondents with a total of 7 or more likes for posts from parties or politicians. The effective sample size is now 468 while prediction accuracy has increased to 70.8% (CI = ±4.2%). It is indicative of better prediction rates by imposing a criterion for how many total political likes a user should have. Accuracy for right/left with this model is now 96%.

Implications of Predictions

The main implication of the results is showing the potential for studying political behaviour in multiparty systems on social media on a large scale. The profiling of individual users through their political "like history" thus lends itself as a tool to study political participation on social media. Through collecting political likes, it becomes possible to profile a significant portion of a national population — in this case 23% of the entire population — with a least one political like, and nearly 1 million with at least seven. In this thesis the ability to predict the voting intention of users will be used to develop other methods for measuring cross-cutting agreement and political homogeneity which are generalizable to other democratic countries with high social media usage.

Due to the non-random drop-out rate in this study, which only ends up including respondents who are active Facebook users, the national population is not perfectly represented. Women, younger people and people with higher education are overrepresented in the samples used for the regression models (see Appendix 5.1-SI). However, it does not seem that any one group is totally left out or overrepresented to a degree that would call the overall results into question. Estimates for predicting the aggregate electoral outcome based solely on political likes are comparable to most opinion polls suggesting that the results can potentially be generalized to the entire Danish population (details in Appendix 5.3-SI). Generalizing findings outside the group of politically active users, one should, however, be attentive of the bias inherent to Facebook as mentioned earlier. There are clear similarities between the sample demographics and those found by Facebook's own Audience Insights[20]

Further, one should also expect users who seek out politicians on Facebook to be slightly more politically active than the rest of the population. With these limitations in mind, and in accordance with studies of other social media platforms (Ceron, Curini & Iacus, 2015), it is possible that the general mechanism of political likes would be reproducible in most open Western multiparty democracies where Facebook has become a central political arena.

Perspectives on Parsimonious Data and Generalization of Digital Traces

The use of traditional survey data combined with a parsimonious strategy that emphasizes theoretically motivated selections and filtering of features can seem at odds with the Big Data oriented methodology laid out in this project. However, such deviations will be necessary. First of all, even if a prediction model is developed for use on very large amounts of data a smaller sample of reliable real world responses or manually labelled data points are required in order to establish a "ground truth" that a machine learning model can be trained on (Řehůřek, 2011, 56). The Big Data aspect of the methods tested in this chapter hinges on the fact that less parsimonious models that used more data points were tested, but shown to be less effective than more parsimonious models that applied filtering based on domain knowledge and common sense (e.g. removing users based on some political likes minimum criteria). Employing a parsimonious approach as demonstrated relates to the previously mentioned notion by boyd & Crawford (2012) that Big Data completely devoid of theory is likely less effective in the social sciences.

[20] (https://www.facebook.com/ads/audience-insights/people?act=41292822&age=18-&country=DK). – Checked December 2017.

Searching for patterns that can predict personal traits within very large datasets is an approach that goes beyond Kosinski and related work. Rather, the trend toward bigger and broader datasets seems to have become the standard for data experiments in the field of computational social science (e.g., Watts, 2014). Increasingly, this ideal has also appeared in commercial data analysis as illustrated by Cambridge Analytica, a data analytics firm drawing on Kosinski et al.'s (2013) work, when it proclaimed to have secured Donald Trump's victory through the collection of "4–5,000 data points on every American" (Tett, 2017).

The field of computational social science has reached a level of maturity that makes it timely to replace the ideal of *broad* data with a parsimonious ideal of *selective* data. While the studies by Kosinski and colleagues should not be compared 1:1 (due to differences in goals and context), it seems fair to note how using only the respondents' single latest political like delivers performance comparable to their best prediction of political attitude built on hundreds of likes (Kosinski, Stillwell & Graepel, 2013; Youyou, Kosinski, Stillwell, 2015) (this project = AUC 0.8 vs. Kosinski et al. = 0.85). Additionally, Theodoridis, Papadopoulos & Kompatsiaris (2015) reach a result of AUC = 0.8 using the same dataset as Kosinski and collegues. Again, this is reporting the left-right AUC value obtained in this project in order to make our results comparable.

Accuracy with *generalizability* is the main advantage of the parsimonious data strategy used for the prediction models in this chapter. Based solely on a limited data scope, consisting of the single latest like per respondent, it was possible to predict multiparty choice with an accuracy of 0.439. The accuracy was lifted above 0.6 by including all likes, and then above 0.7 by imposing a minimum like criteria of 7 likes. The results thus indicate that even a single political like is comparable in accuracy to most multiparty studies in political science, commonly reaching accuracy of around 35%, by combining survey questions on sociodemographics, political values, and opinions toward current issues (e.g. Merrill & Grofman, 1999, Schmidt et al., 2017). While this line of research is not entirely comparable, since political scientists are typically searching for explanation rather than prediction, the predictive power of political likes becomes striking when contemplating the approximately 30 survey questions involved in reaching 35% accuracy.

It seems reasonable to consider why likes predict voting behaviour so dramatically, and so much better than survey results. Referencing major theories in studies of voting behaviour, one could suggest that a like is predictive because it reveals alignment with the ideology of the liked party (Campbell, 1960), the issue taken up (Petrocik, 1996; Nie, Verba & Petrocik, 1999) or the personal traits of the party candidate (Kinder et al., 1980; Ohr & Oscarsson, 2013). Another response to this question is to re-articulate an often-used designation: that likes comprise a generic mechanism for users to show their support. Political likes should be seen as a measure that captures a multitude of the abovementioned — and probably also other — theories for *why* we vote (i.e., ideology, shared issue, or personal identification). This response is in line with both the overall high accuracies reached, which make it difficult to imagine a single theoretical driver, and with the lack of complementary effects seen in model 3, which suggest that we should view likes as encapsulating a number of different motives and preferences.

The high accuracies and lack of complementary effects also indicate that most people are highly selective with their political likes. We should thus not think of political likes as a cost-free interaction that we carelessly direct toward any post that catches our attention, but rather as an interaction form that we apply when we are clearly aligned across one or even multiple axes of preferences. As such, political likes should be seen as a parsimonious measure that condenses a heterogeneous mixture of different motives and individuals' inscription into politics.

This chapter has explained the process of creating prediction models that can reliable show the voting intention of a given Danish Facebook user, assuming of course that the user has interacted with content from political pages. However, since nearly a million users have made at least 7 likes on posts from political pages over a 4-year period, at least in the data collected for this project, the approach can be reliably used on the general public. The purpose has been to show that these political likes are a solid indicator of a user's political stance. Using this information, the next chapter will present techniques for calculating political homophily and agreement/disagreement from interaction with content and discussions in comment threads.

Chapter 6. Calculating Homophily, Agreement and Disagreement in Discussions

The purpose of this chapter is to build on the results from chapter 5 in order to construct methods that can be used to determine levels of political homophily and of agreement/disagreement for a given discussion.

As determined in previous chapters, social media bring specific issues to the forefront of political communication research, namely how networked information flows curated by a mix of actors relates to the political preferences of the individuals who make up the general public on the digital platforms. Chapter 5 has laid out a method for estimating the political preferences of users. This chapter seeks to translate aggregated interaction patterns related to these political preferences into single measures that can help reveal the contentious nature of a public news piece posted on Facebook and its ensuing discussion. One of the most central concerns with respect to how political preferences influence information flows is political polarization and de-polarization. As mentioned in the previous chapters, polarization is usually viewed as potentially detrimental to democracy. The relation between political polarization and de-polarization will be discussed in later chapters in light of the final results of the analysis. In this chapter the focus is on establishing measures that can reliably be used to analyse political patterns related to polarization and de-polarization of any given discussion. A discussion in this study is defined as a post created by a public Facebook page to which users contribute with reactions and comments. A discussion includes all potential interactions such as users' interactions with content through reactions and comments, but also among users through reactions and replies made to comments.

As stated in chapter 3 political polarization can be represented in two forms: 1) as increased isolation of political groupings (increased political homophily), and 2) as lack of recognition among groups with differing views (heavy political disagreement). This chapter seeks to shine light on these two kinds of polarization by establishing measures that pertain to individual discussions. The first, *political homophily,* is the simplest because it does not have to take multiple flows of interaction into account. It should simply measure the degree to which all users who participate in a discussion (post) are likely to be politically likeminded. The other measure, *political disagreement*, is more complicated because it has to take into account how two or more politically likeminded groupings that participate in a discussion behave together. For this reason, political disagreement will be split into two measures: 1) *initial political disagreement* and 2) *subsequent agreement*. The first is to be calculated based on users' interactions with the content and the second will be determined by users' interactions among one another. The logic behind all three measures will be explained in the rest of this chapter.

It is important to note that the measures created in this chapter are, by themselves, only indicators of patterns pertaining to polarization and de-polarization and must be utilized together with patterns revealed by other pieces of information for a thorough analysis of political polarization to be realized. These will be added in the following two chapters.

Political Likes Vector

In order to demonstrate the potential universal application of methods developed in this thesis, this chapter will utilize data from New Zealand. The final analysis will focus on the Danish public as it has more data available, however distributions of the three measures will be compared between the two countries in order to substantiate their transferability. As explained earlier, not every politician has a public Facebook page. For New Zealand it comes to a total of 121 pages that represent either a politician or a political party.

Chapter 5 showed that political preference of a user is best determined by simply counting the number of positive reactions to posts made by a party, and all politicians from that party, that the user has made. Average best prediction accuracy is obtained for users for whom the sum of total reactions is at least 7. The number of positive reactions for any given users in the direction of a political party should then be normalized by the total sum of positive reactions pertaining to that user. This procedure is illustrated in Equation 6.0 wherein a user is given by u with v being a vector of positive reactions to political parties. Thus, a user is represented by a vector where each element corresponds to the proportion of likes that has gone towards a particular party. Throughout this study the user is represented as a vector to better accommodate the less absolutistic workings of MMP systems. If a user has liked two or three parties equally then that user will be represented as such, instead of being reduced to a supporter of a single party or block. A visual representation of the user vector can be found in Appendix 6.0-SI. This also helps accommodate some of the error in the prediction model developed in the previous chapter (Figure 5.1). As was shown, users who have more than 90% positive reactions towards are single party are much more likely to actually vote for that one party compared to one with only 50% towards a single party. It is possible to infer from this that users who divide their likes more equally among parties are more split between political positions. By always treating a user's voting intention as a vector of support towards multiple parties, the inaccuracy pertaining to actual voting intention is preserved within the representation itself. Equation 6.0 denotes the user vector.

$$u_i = \frac{v_i}{\sum_{j=1}^{N} v_j} \left[\sum_{j=1}^{N} v_j \geq 7 \right]$$

EQUATION 6.0

Applying this to all users in the New Zealand dataset ends up with a total of 271,992 politically significant users in New Zealand. It is then observed how many and how often these users appear on the New Zealand public pages. By counting how many actions (reactions, comments, comment-reactions etc.) were taken by our politically significant users compared to the full number of actions, an average political user penetration (later denoted as userPolPen) of approximately 56% on public pages is reached. Values of userPolPen are of course not evenly distributed, and some pages, typically ones with low amounts of political content, have much lower penetration rates.

Estimating political homogeneity

With a single user represented by the vector denoted in Equation 6.0, the intention is to estimate the political homogeneity of a discussion using the aggregate of all users who participate. Nikolov, Lalmas, Flammini & Menczer (2019) deal with a similar problem in their research, where instead of a user being represented by the proportions towards political parties they support, a user is represented by how many times they have shared links from specific web domains. In their study they estimate the homogeneity bias simply from the entropy of a single user vector. This approach misses two aspects, both of which are important when the user vector represents affiliation with political parties: 1) it does not account for the fact that parties vary in size (i.e. in New Zealand one would expect Labour and National to represent a very large fraction of the total vote), 2) some parties are more likely to support each other, which should resonate with the voters (i.e. it is more likely that a Labour voter will show some support to the Green Party compared to ACT). To address these two aspects, this study will apply a slightly more complex approach, but also seek to make it more empirically intuitive.

In order to calculate political homogeneity for a single discussion the political distribution of users for that discussion will be compared to the grand average of all users. The intuition is that the average political distribution of all users will represent the maximum *empirical* entropy. By comparing the grand average distribution to that of a given discussion the distance between them will give an indication of how politically homogeneous a discussion is. For this reason, a base function for this method will be one that calculates the distance between two aggregated user vectors.

The calculation for the grand average and the aggregate of users for a single discussion essentially has the same form as that of a single user. The values for the user vectors are averaged on the second axis so that it has the form g in Equation 6.1.

$$g_j = \frac{\sum_{i=1}^{N} u_{i,j}}{N}$$

Equation 6.1

For a single discussion, the users represented by g include only those who participate on the post, either through reactions or comments. For the national average *g* includes all users and will be denoted as *natAvg*.

Next a formula for calculating the distance between two vectors is needed. There are many standard approaches to this with one of the most popular being the *cosine distance* (Řehůřek, 2011), which is given by the form *COS* in Equation 6.2*:*

$$cos = \frac{\sum_{i=1}^{N} A_i B_i}{\sqrt{\sum_{i=1}^{N} A_i^2}\sqrt{\sum_{i=1}^{N} B_i^2}}$$

EQUATION 6.2

However, the standard formula needs to be updated to accommodate the specific needs of this study. Simply taking the distance between the two groups (i.e. participants from discussion g vs. natAvg) would not take into account that some political parties are more similar than others. In New Zealand for example if the biggest contributor to the distance is the difference in the proportion of Green and Labour voters this would be less significant than if the difference was between Green and National voters. Thus, one would like to calculate an estimate for the covariance between positive reactions towards each pair of parties. This is done by going back to the political pages to calculate the covariance matrix where A and B correspond to a pair of political parties across all user vectors (Equation 6.3):

$$Mcov_{A,B} = \frac{1}{N}\sum_{i=1}^{N} A_i B_i - \frac{1}{N^2}\left(\sum_{i=1}^{N} A_i\right)\left(\sum_{i=1}^{N} B_i\right)$$

EQUATION 6.3

Furthermore, it is desirable to account for the variable size of political parties. Low entropy cases that are heavily biased towards very small parties should considered slightly more homogenous compared to the largest parties. To put more emphasis on small parties the inverse of the national grand average, *invNatAvg* (Equation 6.4) is considered*:*

$$invNatAvg_i = \frac{natAvg_i}{1}$$

EQUATION 6.4

The weighted covariance matrix thus takes the form *Mcov* shown in Equation 6.5.

$$Mcov_{i,j} = \prod_{i=1}^{N} log_{(invNatAvg_i Mcov_{i,j})+1}$$

EQUATION 6.5

The original cosine distance function (COS) it then updated by adding the weighted covariance matrix to create a non-Euclidean inner product. The final formula for calculating the political homogeneity for a discussion has the following form *polHom*, where A represents all the all participants given by the previous Equation 6.1. polHom is shown in Equation 6.6.

$$polHom = \frac{\sum_{i=1}^{N}(A_i \sum_{j=1}^{D} Mcov_{i,j})(natAvg_i \sum_{j=1}^{D} Mcov_{i,j})}{\sqrt{\sum_{i=1}^{N}(A_i^2 \sum_{j=1}^{D} Mcov_{i,j})}\sqrt{\sum_{i=1}^{N}(natAvg_i^2 \sum_{j=1}^{D} Mcov_{i,j})}}$$

EQUATION 6.6

Equation 6.6 allows us to collapse the multiparty vector space into a single number that indicates the political homogeneity of users. A discussion of course needs to have enough participants. Using the method in the following chapters will be limited to posts that have at least 10 participants and at least 40% political penetration (40% users with a history of at least 7 positive reactions to politicians).

The measure of political homogeneity builds on the previously mentioned general idea that a homogeneity bias can be obtained from the entropy of this kind of user vector. Furthermore, the face validity of the calculation is apparent by looking at the top and bottom of Facebook pages that have the highest and lowest levels of homogeneity. Politicians who generally seek less broad appeal tend to have the most homogenous Facebook pages, which will be explored more in detail in chapter eight. The measure aligns well with the general expectation that specialized political pages have the highest levels of political homogeneity while media pages that are least related to politics have the lowest levels. For these reasons it is assumed to be a fairly reliable measure that does not need to be evaluated further. This however is not the case with political disagreement/agreement, which will require more assumptions to be made.

Estimating initial political disagreement and subsequent agreement

There are many ways for users to convey whether they agree with one another by commenting specifically on each other's arguments. However, this study is interested in finding a generic mechanism that can be used as an indicator of overall political disagreement/agreement. Instead of finding patterns pertaining to agreement and disagreement within the comments themselves, which can be an extremely complicated problem, this study strives for a more parsimonious approach. This part wants to take advantage of the fact that Facebook employs affordances that contain both positive and negative reactions as well as comments on multiple levels of interaction. It builds on the intuition that if users who choose certain types of responses can noticeably be divided into groups that corresponds to distinct political factions (within the multiparty vector space), that can be an indicator that users are positioning themselves differently based on political affiliation and thus represent a kind of disagreement. Again, this can happen in multiple flows of communication. Three measures are devised: *disCom*, *disAs* and *subAgree*[21].

The value of disCom functions as a measure of political disagreement based on users' initial reaction to a post. The calculation entails separating users into two groups: 1) those who "like/love" the post and 2) those who comment on the post without clicking "like/love". The formula is more or less identical to the function for obtaining the political distance between two aggregated user vectors used to calculate polHom. The formula for calculating the disCom has the following form with A and B being the two groups described above, where N is the parties in the aggregated user vector and D represents the same parties in the covariance matrix.

$$disCom = \frac{\sum_{i=1}^{N}(A_i \sum_{j=1}^{D} Mcov_{ij})(B_i \sum_{j=1}^{D} Mcov_{ij})}{\sqrt{\sum_{i=1}^{N} A_i^2 \sum_{j=1}^{D} Mcov_{ij}}\sqrt{\sum_{i=1}^{N} B_i^2 \sum_{j=1}^{D} Mcov_{ij}}}$$

EQUATION 6.7

Thus, a high value for disCom should be equal to a high level of initial, political disagreement over a post.

The disAs value is similar to disCom. It describes political disagreement over the content of a post. But here the distance between two other groups is measured: 1) those who "like/love" the post and 2) those who click "angry/sad" to the post. Calculating the disAs relies on the exact same formula as disCom. A high value for disAs is equal to a high level of initial political disagreement over a post.

With subAgree the attempt is made to measure what happens in the interaction between users in the comment section. This can be called subsequent agreement and consists of positive reactions to comments with the purpose of measuring agreement between users who have different political preferences. This means that by measuring the distance

[21] The variable names are mapped as follows: disCom = disagreement through comment only vs. comment + like. disAs = disagreement through angry + sad. subAgree = subsequent agreement.

between the user who wrote the comment and the users who reacted positively ("like/love") to the comment, one gets an estimate of the level of subsequent agreement between people with different political preferences. For subAgree roughly the same formula as for disCom and disAs can be used, with a small adjustment. A is now the single user who wrote the comment and B is the aggregated group of users who reacted positively to it. The operation is then performed for all comments C to determine the value pertaining to a single discussion, shown in Equation 6.8.

$$subAgree = \sum_{l=1}^{C} \frac{\left(\frac{\sum_{i=1}^{N}(A_i \sum_{j=1}^{D} Mcov_{ij})(B_i \sum_{j=1}^{D} Mcov_{ij})}{\sqrt{\sum_{i=1}^{N} A_i^2 \sum_{j=1}^{D} Mcov_{ij}}\sqrt{\sum_{i=1}^{N} B_i^2 \sum_{j=1}^{D} Mcov_{ij}}}\right)_l}{C}$$

EQUATION 6.8

A high value for subAgree should then be equal to a high level of subsequent agreement across political lines. Additionally, subsequent agreement can also be obtained for a simple comment by not summing over C (Equation 6.9):

$$subAgree_c = \left(\frac{\sum_{i=1}^{N}(A_i \sum_{j=1}^{D} Mcov_{ij})(B_i \sum_{j=1}^{D} Mcov_{ij})}{\sqrt{\sum_{i=1}^{N} A_i^2 \sum_{j=1}^{D} Mcov_{ij}}\sqrt{\sum_{i=1}^{N} B_i^2 \sum_{j=1}^{D} Mcov_{ij}}}\right)_l$$

EQUATION 6.9

Testing measures of political agreement and disagreement

Compared to the method for calculating political homogeneity disagreement is less straightforward. It cannot be assumed that people necessarily use Facebook in the way it is imagined for the disCom, disAs and subAgree measures. It is possible that the use of emoji responses and comments are too subjective to reveal any true patterns at all. For this reason, it is necessary to evaluate whether interaction patterns comprised in disCom, disAs and subAgree correspond to the political affiliation of the users.

For illustrative purposes the variables are shown as part of the communications flow as illustrated in Figure 1.

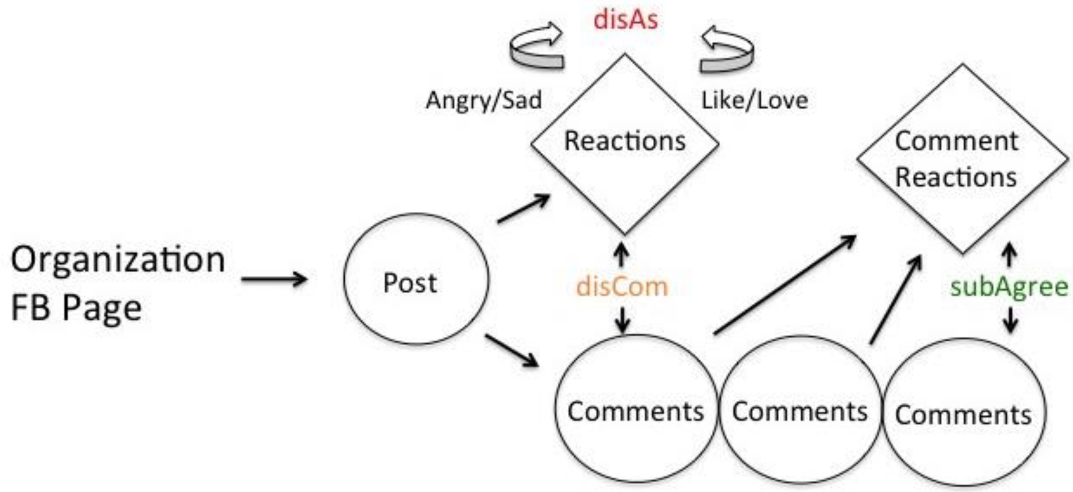

Figure 6.0: Communications flow with disCom, disAs and subAgree

To be able to check whether users are actually reacting in a politically significant way, 1.200 posts using the categories *political, non-political* or *proto-political* are manually labelled by two researchers (thesis author + fellow researcher). A label is assigned depending on the content of the post independently of any other data related to that post. It is hypothesized that if people are reacting to posts in a politically significant way, then posts that contain political content should have very different reaction patterns than non-political posts.

As mentioned previously, not all posts have an equally high penetration of active users with politically significant profiles. Furthermore, common sense dictates that for example a post with only one reaction and one comment might provide very unreliable results. Therefore, in calculating disCom, disAs and subAgree a post must pass a certain condition or the value will be Null. The conditions are shown in Table 6.0. The final dataset to be used for the rest of this study is the one called *final selection*. The second column in the table designates the number of posts that match the condition.

Selection	Number of non-Null posts	Condition
all posts	N = 56.782	No condition
disCom	N = 12.170	Minimum userPolPen = 40% AND minimum 10 politically significant users in each group (“like/love” vs. comment with no “like/love”)
disAs	N = 6.599	Minimum userPolPen = 40% AND minimum 10 politically significant users in each group (“like/love” vs. “angry/sad”)
subAgree	N = 9.488	Minimum userPolPen = 40% AND minimum 10 politically significant users in each group (commenter vs. positive comment reactions)
final selection	N = 14.455	At least one of the variables disCom, disAs or subAgree must be not Null.

Table 6.0: Conditional filtering of data samples

Political posts are those connected to political parties, government, election, politicians, policies, known political issues or any other concept explicitly related to politics. Stories revolving around statements and proposals made by politicians and parties are the most typical political posts. Non-political posts are those that by no means have any political implication. For instance, the posts that are about sports and celebrities were labelled as non-political posts in our study. Proto-political posts are those that do not refer explicitly to political concepts but are related to issues that could easily take a political turn.

Table 6.1 contains examples of some labelled posts.

Example	Post content	Post link	Explanation
Political	Bill English talks about national's child poverty target, urban planning and last night's debate	https://www.facebook.com/Stuff.co.nz/videos/10155730056819268/	The story is directly about the leader of the National party in a political context.

Proto-political	#LIVE: Police hold a brief middle-of-night (UK time) press conference in the wake of the suspected terror attack at an Ariana Grande concert that has resulted in at least 19 deaths	https://www.facebook.com/1NEWSNZ/videos/10154439396981218/	This is a significant and sad story, that can have important political implications, but no explicit reference to politics is made in the news piece.
Non-political	Thieves took irreplaceable photos of Anna Geddes' deceased four-year-old daughter, Brydie, during a burglary at her Christchurch home.	https://www.facebook.com/thepress/videos/10154511169647618/	This story is not related to any prevalent political issues.

TABLE 6.1: CODING EXAMPLES

Posts that are explicitly related to politics, users are expected to more clearly position themselves politically in agreement or disagreement over the main message in the news piece.

Values of disAs and disCom are not distributed equally. In order to ensure an equal distribution of high, middle and low values of disCom and disAs, posts are sampled as illustrated in Figure 6.1. It includes taking 250 random posts with disCom values above 0.5 and the same with disAs. Lastly, 350 random posts with non-Null values of disCom and the same with disAs are taken, which comes to a total of 1200 posts.

As a last step, two coders using the same guidelines as above independently recoded 100 random posts. Calculating the pairwise intercoder agreement using Krippendorfs alpha yields α = 0.946.

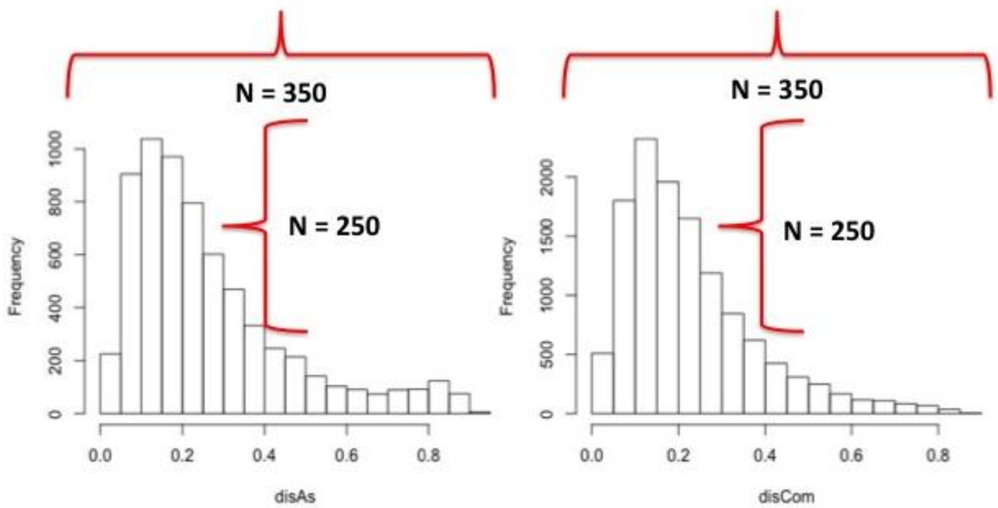

FIGURE 6.1: HISTOGRAMS FOR DISCOM AND DISAS – SAMPLING STRATEGY SHOWN

Results

High levels of disagreement over political content

In order to show the significance of agreement/disagreement patterns, we start by comparing the means of the three groups for the disCom and disAs variables. Table 6.2 contains the means and standard deviations for all three variables across for political, proto-political and non-political posts. Political posts have significantly higher averages for both disCom and disAs values. For disCom proto-political posts also seem to have higher values than non-political posts, but since there are much fewer proto-political posts this is not completely reliable. The significant difference between non-political and political posts is confirmed using Welch two-sample T-test shown in Table 6.3.

Samples	**disCom t-value**	**disCom p-value**	**disAs t-value**	**disAs p-value**	**subAgree t-value**	**subAgree p-value**
non-pol - pol	-21.382	2.2E-16	-17.119	2.2E-16	8.8519	2.2E-11
pol - proto-pol	6.9899	1.96E-09	6.8657	3.10E-08	-3.5699	0.0007901
non-pol - proto-pol	-2.4733	0.0164	-0.74313	0.4614	0.68565	0.4959

TABLE 6.3: WELCH TWO-SAMPLE T-TESTS FOR CONTENT TYPE ON DISCOM, DISAS AND SUBAGREE

Content Type	**disCom mean**	**disCom std.dev**	**disAs mean**	**disAs std.dev**	**subAgree Mean**	**subAgree std.dev**	**N posts**
non-pol	0.240	0.167	0.335	0.228	0.543	0.162	578
pol	0.499	0.219	0.659	0.216	0.445	0.136	515
proto-pol	0.306	0.182	0.367	0.242	0.527	0.141	102

TABLE 6.2: MEANS AND STANDARD DEVIATIONS FOR CONTENT TYPE ON DISCOM, DISAS AND SUBAGREE

It is worth noting that all groups have fairly high standard deviations on disCom and disAs. This demonstrates that while the average difference between political and non-political is extremely significant there are some non-political posts that cause political disagreement. It suggests that topics, which appear non-political on the surface, might have latent political qualities.

Users' initial reaction to a post is shaped by the political standpoint of the user if the content is political, and it shows that disCom and disAs work as reliable measures for initial political disagreement. Through the inclusion of both disCom and disAs it is possible to show that emoji responses, which are sometimes considered ambiguous, do in fact correspond to the political alignment of users on average.

Reaching agreement

This part covers the relationship between disCom/disAs and subAgree. We can see already from Table 3 that average subAgree is significantly lower for political posts than non-political ones. However, in order to test the actual relationship three ordinary least squares regression models are run: *subAgreeDisComMod, subAgreeDisAsMod* and *subAgreeFullMod*. The two first ones model subAgree as a function of disCom and disAs respectively, and the last one contains both disCom and disAs. All models are accompanied by a selection of control variables such as total number of reactions, comments etc. They are shown in Tables 6.4, 6.5 and 6.6.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	0.537477463	0.007450521	72.13958233	0	***
disCom	-0.089419072	0.011591057	-7.714487941	1.35E-14	***
totalLike	3.57E-06	3.83E-06	0.93243216	0.351138653	

totalLove	-2.25E-05	7.95E-06	-2.824969243	0.004739091	**
totalSad	5.21E-05	1.10E-05	4.744934231	2.12E-06	***
totalAngry	2.41E-05	1.15E-05	2.087946182	0.036831194	*
totalShares	-5.03E-06	7.25E-06	-0.69382967	0.487807233	
totalReactions	-1.55E-06	3.05E-06	-0.506603203	0.612445874	
totalComments	3.24E-05	6.86E-06	4.718966245	2.41E-06	***

TABLE 6.4: SUBAGREEDISCOMMOD (OLS)

Formula: subAgree ~ disCom + totalLike + totalLove + totalSad + totalAngry + totalShares + totalReactions + totalComments.

P < *** 0.001 ** 0.01 * 0.05

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.557910036	0.011427981	48.81965104	2e-16	***
disAs	-0.108747428	0.012441909	-8.740413094	3.31E-18	***
totalLike	2.79E-06	4.97E-06	0.562663806	0.573694053	
totalLove	1.43E-05	1.07E-05	1.333180648	0.182545285	
totalSad	3.24E-05	1.44E-05	2.24948758	0.024533398	*
totalAngry	-1.19E-05	1.50E-05	-0.789653155	0.429775211	
totalShares	-1.25E-05	9.92E-06	-1.262412368	0.206870968	
totalReactions	9.72E-07	3.86E-06	0.252107035	0.800970745	
totalComments	2.04E-05	8.78E-06	2.326134949	0.020059005	*

TABLE 6.5: SUBAGREEDISASMOD (OLS)

Formula: subAgree ~ disAs + totalLike + totalLove + totalSad + totalAngry + totalShares + totalReactions + totalComments.

P < *** 0.001 ** 0.01 * 0.05

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.559527336	0.011850939	47.21375452	0	***
disCom	-0.065797825	0.019505081	-3.373368378	0.000750494	***
disAs	-0.091489049	0.016123734	-5.674184859	1.50E-08	***
totalLike	1.99E-06	4.99E-06	0.399383064	0.689634969	
totalLove	1.12E-05	1.08E-05	1.043535507	0.296771319	
totalSad	2.42E-05	1.45E-05	1.669049142	0.095195718	
totalAngry	1.35E-06	1.55E-05	0.087270244	0.930461622	
totalShares	-5.92E-06	1.01E-05	-0.586937991	0.557282634	
totalReactions	-1.09E-06	3.84E-06	-0.284798444	0.775815158	
totalComments	4.04E-05	9.04E-06	4.468083707	8.14E-06	***

TABLE 6.6: SUBAGREEFULLMOD (OLS)

Formula: subAgree ~ disCom + disAs + totalLike + totalLove + totalSad + totalAngry + totalShares + totalReactions + totalComments.

P < *** 0.001 ** 0.01 * 0.05

In all three models disCom and disAs are negatively correlated with subAgree to a statistically significant degree (e.g. disCom estimate in subAgreeDisComMod = -0.089419072). This means that high levels of political disagreement over the content of a post affects the second step in the communication flow yielding lower levels of subsequent agreement. However, it is worth noting that, while statistically significant, the correlation is not extremely strong. It can also be seen in Table 6.2 that the difference between the means of political and non-political is much lower for subAgree than for disCom and disAs. This suggest that there are many additional parameters that will influence whether a discussion might produce agreement across political lines.

Disagreement during the election campaign

As election campaigns in liberal democracies are often quite short and intense, the media typically delivers increased amounts of political content during that time. With a surge in political content published by mainstream media outlets one would expect higher levels of political disagreement over content on Facebook. In Figure 6.2 it shows that the average levels of disCom and disAs are increasing towards the election date, after which they drop again. Similarly, subAgree reaches a low point at the same time disCom and disAs are at their highest. It shows that initial political disagreement is highest around election time with subsequent agreement being at its lowest. However, it is important to notice that initial disagreement and subsequent agreement aren't always moving in tandem. In the middle of 2016 it shows that disCom and disAs are at relatively high levels while subAgree is at its highest point. It suggests that even though subAgree is negatively correlated with disCom and disAs on the general level, there are cases where users are reaching subsequent agreement despite much initial disagreement. The disCom, disAs and subAgree measures might help point us towards the issues that either unite or polarize people in a two-step flow.

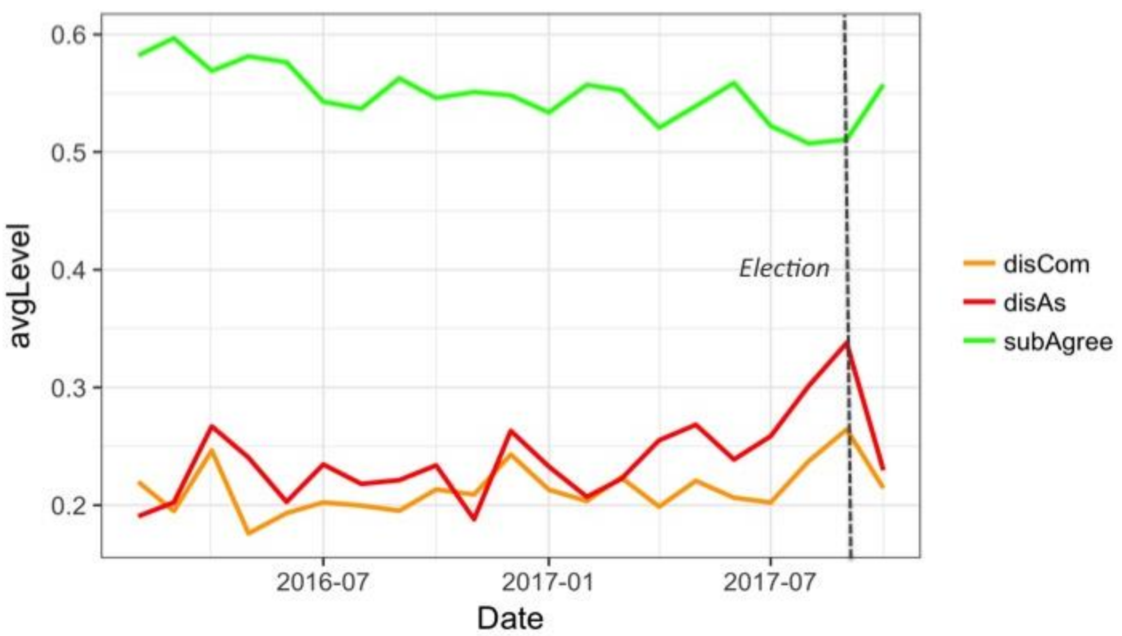

FIGURE 6.2: TIMELINE FOR DISCOM, DISAS AND SUBAGREE

Further Exploration: Distribution and Min/Max Examples

The main purpose of this paper has been to show that there are clear patterns pertaining to how users position themselves politically in a two-step flow of responses to news pieces on Facebook conceptualized as initial political disagreement and subsequent agreement. It is beyond the scope of this paper to fully explore the potential reasons for why particular content attain different combinations of values of disCom, disAs and subAgree. However, there is potential in further using these values to group, categorize and analyse public Facebook discussions, both quantitatively and qualitatively. This section includes a few examples of how the computational framework can be used for further exploration. This is done by manually looking at some of the posts that receive very high disCom or disAs, but very low subAgree (upper left corner of Figure 6.3) as well as those that score relatively high on both disCom/disAs and subAgree (upper right corner of Figure 6.3).

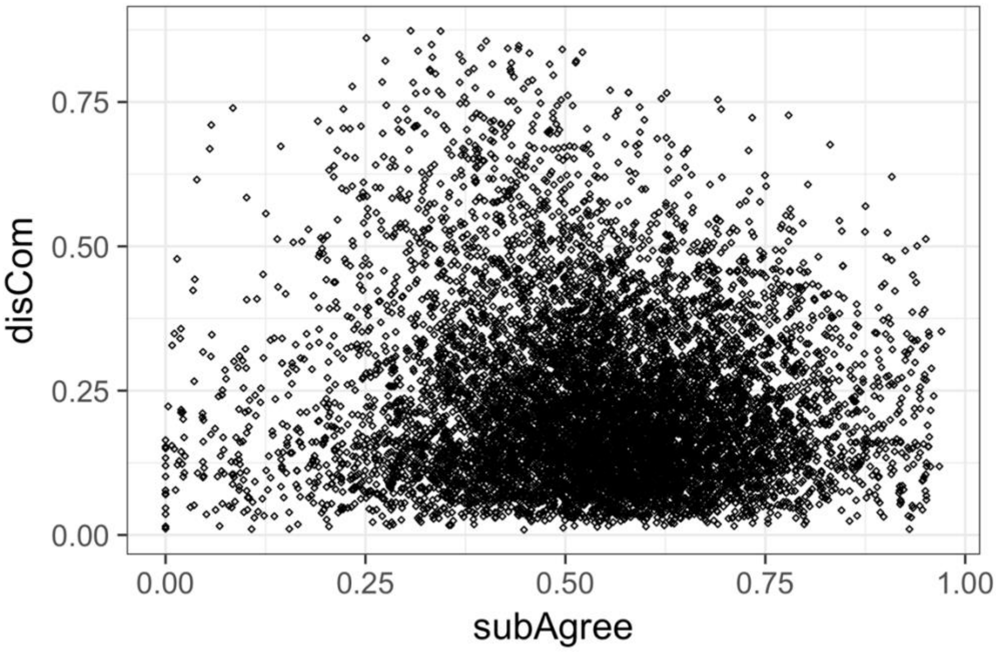

FIGURE 6.3: SCATTERPLOT FOR DISCOM AND SUBAGREE

Top 5 posts with high initial disagreement and low subsequent agreement

Table 6.7 contains some examples of posts that have very high disCom or disAs values while retaining a relatively low subAgree (Those closest to the upper left corner of Figure 6.3).

One can see that all posts are strongly framing a specific political party in terms of what they do and say, such as: "Pm announces…", "Labour tidies up…", "Ardern takes initiative…". Interestingly two out of these five posts are about the financial plans drawn up by National and Labour, which suggests that their main economic policies sustain political division. A proposal about home improvements made by Green Party leader James Shaw also ends up with very low subsequent agreement. This could be of interest since home improvements might intuitively be topic where one would expect more political unity across the spectrum.

Message	Post Link	disAs	disCom	subAgree
pm tours hawke's bay and announces economic plan national says its five-point plan announced today will bring sustained economic success. bill English back in town.	http://www.nzherald.co.nz/hawkes-bay-today/news/article.cfm?c_id=1503462&objectid=11923536	0.809	0.861	0.151
labour tidies up tax policy labour tidies up its tax policy. labour delays tax changes.	http://www.nzherald.co.nz/hawkes-bay-today/news/article.cfm?c_id=1503462&objectid=11922151	Null	0.669	0.055
labour lays out financial plan with billions more for health, education labour has put its money where its mouth is - what's your take on their announcement?	https://www.stuff.co.nz/national/politics/94879965/labour-lays-out-financial-plan-with-billions-more-for-health-education	Null	0.615	0.039

comment: ardern takes the initiative jacinda ardern was the winner of the leaders' debate in christchurch last night in her most spirited and interesting clash yet with bill English.... "Jacinda ardern was the winner of the leaders' debate in Christchurch last night in her most spirited and interesting clash yet with bill English." do you agree? have your say in our poll, which is included in Eileen Goodwin's opinion piece.	https://www.odt.co.nz/news/election-2017/comment-ardern-takes-initiative	Null	0.740	0.084
'housing kills more people than our road toll' – greens pledge $500 million to insulate homes James Shaw says there would also be warrant of fitness rules for rentals under a plan for warm, dry homes. Mr Shaw said poor quality housing "kills more people than our road toll."	https://www.tvnz.co.nz/one-news/new-zealand/watch-housing-kills-more-people-than-our-road-toll-greens-pledge-500-million-insulate-homes-if-in-government	Null	0.673	0.144

TABLE 6.7: EXAMPLES OF POSTS WITH HIGH DISCOM/DISAS AND LOW SUBAGREE

Top 5 posts with high initial disagreement and high subsequent agreement

The posts, shown in Table 6.8, that start out with high initial disagreement and then ends up with relatively high levels of subsequent agreement are topically quite diverse.

Two of them are related to U.S. politics, which might suggest that NZ citizens can easily unite over their relation to the U.S. One also sees people uniting over the stepping down of Green Party leader Metiria Turei, who admitted having defrauded the NZ social benefits system when she was younger. In a more positive way for Greens, users also seem to come together over Green MP Chloe Swarbrick's decision to join a weapons expo protest.

These are just a few examples and no broad trends can be extracted from them. However, by expanding the analytical frame either qualitatively or quantitatively it might be possible to learn more about how or why users reach agreement over political (or non-political) issues in a public online forum such as Facebook.

Message	Post Link	disAs	disCom	subAgree
former green party co-leader metiria turei's political career likely to be over #breaking metiria turei could be looking for a new job at the end of the night.	http://www.nzherald.co.nz/nz/news/article.cfm?c_id=1&objectid=11925699	0.665	0.527	0.815
southland's perspective on the us elections americans in southland keeping a close eye on the us election tim newman last updated 16:31, november 9 2016 staff will it be donald trump or hillary clinton for us president? an american woman living on a dairy farm near otautau says the us election is "crazy".elisa ternstrom, born and raised in or... "it's crazy - it's like a reality tv show with the kardashians." americans living in southland give us their thoughts on the us election... have you been following the coverage?	http://www.stuff.co.nz/southland-times/news/86276306/americans-in-southland-keeping-a-close-eye-on-the-us-election	Null	0.676	0.831
pm bill english on waitangi and his talk with donald trump mike puru and trudi nelson talk with prime minister bill english on waitangi weekend and his chat with united states president donald trump in the weekend. if you were in bill english's shoes and received a call on your cellphone from us president donald trump, what topics would you raise? mikeandtrudi talked with the nz prime minister this morning.	http://www.radiolive.co.nz/PM-Bill-English-on-Waitangi-and-his-talk-with-Donald-Trump/tabid/506/articleID/136262/Default.aspx	Null	0.723	0.734
new green mp chloe swarbrick turns out to support 'weapons expo' protests in wellington protesters from around the country have gathered in the hopes of disrupting the delegates. "i think it’s really crucial that we do things like protest....because otherwise nothing is ever going to change."	https://www.tvnz.co.nz/one-news/new-zealand/crucial-we-protest-new-green-mp-chloe-swarbrick-turns-support-weapons-expo-protests-in-wellington-v1	0.795	0.737	0.695
kiwis in oz: stop whinging migrants should add to a country. the simple reality is, if you don't like the way things are run don't go. #mikesminute	https://www.facebook.com/newstalkzb/videos/1126992914010589/	Null	0.666	0.729

Table 6.8: Examples of posts with high disCom/disAs and high subAgree

Utility of Political Disagreement Measures

The purpose of this chapter has been to present the main techniques used to calculate political homophily and agreement/disagreement for any given public Facebook post. Additionally, the chapter has explored some patterns related to the proposed measures, especially those pertaining to agreement/disagreement, in order to verify that they can be used to analyse actual political behaviour.

In chapter 8 the aim is to examine patterns of cross-cutting agreement meaning agreement that happens across political oppositions. As was demonstrated in this chapter, getting a solid indicator for cross-cutting agreement is difficult using either of the disCom or subAgree measures independently; they have to be used in combination. To make analysis more manageable it would be useful to combine disCom/disAs and subAgree into a single measure, however this will not be done until chapter 8 because it is easier to grasp when employed in the context of the final analysis.

The final analysis will explore how political homophily and agreement/disagreement relate to public opinion in the Danish public on Facebook with respect to various spaces, topics, sentiments and periods. Before this can be accomplished, it is necessary to establish a method for sorting and categorizing posts based on which type of space it appears in, the topic that it discusses, and the language used by the users in response. The next chapter will present the page categories, topics and sentiment analysis strategies used to accomplish this.

Chapter 7. Page Categories, Topics and Sentiments

The purpose of this chapter is to describe and test methods for determining the category of pages on which a discussion might take place, the topic of discussion and the sentiment of a discussion. The results obtained through the methods in this chapter will later be combined with information from chapter 6 in order to analyse the distribution of political homogeneity and disagreement across spaces, topics and sentiments in chapter 8. One thing that sets this chapter apart from the two previous chapters is that each method is more restricted to a particular language/culture. They can technically be applied in any country, but not without additional, manual preparation of data (e.g. determining the sentiment of a text requires some data to be prepared by human coders[22]). For this reason, and to make the full analysis more focused, the methods described here will be applied only to the Danish dataset.

Page Categories

Designating categories for pages within each data collection is the simplest out of the three (page categories, topics and sentiments, data preparation) steps in this chapter.

It was mentioned in chapter 4 that the Danish dataset contains thousands of public Facebook pages. Each page can be considered its own space, its own little corner of Facebook, which greatly influences who the participants are as well as their expectations and subsequent behaviour. However, for the purpose of analysing broad trends and general patterns of potential polarization and de-polarization in the Danish Facebook public it can become a bit problematic to consider each page as its own unique space. As was mentioned in chapter 4 all pages already correspond to a specific collection of either political pages, media pages, local pages, union pages or public organization pages. These

[22] A few languages such as English can be considered an exception to this restriction because similar classifiers of sentiment already exist. In practice though, the application and preparing of additional models is still required.

collections can be useful as categories; however, they can also obscure some significant differences within the categories, especially for a very broad and diverse collection such as media pages. It is desirable to categorize pages at a meso level between the macro level of each data collection and the micro-level of each individual page.

The approach for dividing Facebook pages into categories pertaining to the type of page it represents can best be described as heuristic. Two of the data collections, political pages and local pages, already have inherent meso level categories from the way the pages were collected. Political pages, be it individual politicians or party pages, all correspond to the political party they represent, and thus the page categories for political pages will consist of each of the parties in parliament during the period captured in the data collection. Local pages were collected by searching for pages that represented local municipalities (communes) around the country. Thus, page categories for local pages correspond to any of the 98 Danish communes that a page might represent.

In Denmark labour unions are organized such that each union traditionally represents a specific group of workers (e.g. transportation personnel, nurses, psychologists). Some are naturally bigger than others, but most unions also belong to an umbrella organization that is responsible for negotiating the overall conditions and rules of employment with public and private institutions. Page categories for unions are those that correspond to these umbrella organizations. The umbrella organization LO for example, contains most unions that are involved with manual labour and trades. FTF is made up of unions that represent nurses, social workers and teachers and AC contains unions for academic professions across all fields. The union system is largely influenced by tradition and anyone can join any union even if it does not typically represent their profession. A handful of unions make it their mission to be independent of professional traditions and are not associated with the umbrella organizations. These will be given the label: Independent.

Media pages is the largest of the five data collections even though it contains the second lowest number of individual pages (137). Dividing these into a dozen categories can make it significantly easier to navigate the data load. The choice of categories will build on the author's experience as a native Dane and media scholar. The focus of the analysis is on very broad and clearly observable trends and it is assumed that any bias in choosing the categories of the pages should not impact the general trends too much. Furthermore, the categories are fairly broad and designed to fit the general expectation of the average Danish person. Some pages could potentially be put in more than one category, but in that case it will only carry the one category that is the best fit. The main approach can best be described as phenomenological and heuristic meaning that a page will be put into the category that best describes what sets the news content of the organization apart from other media outlets.

The following 13 media categories are conceived: *Business, Culture, Debate, General News, Infotainment, Left Leaning News, Right Leaning News, Lifestyle, Local News, Political News, Sports* and *Tabloid*. A small selection of pages that do not fit into any category will be given the label *Other* and will be omitted from some analyses.

Some categories are self-explanatory such as Business, Tabloid and Sports. Right and left leaning news are those media outlets, which are known to either promote certain political views or simply be overwhelmingly popular with either right- or left-wing voters. Political News are those that specialize in political content, but are considered to be mostly neutral, which can actually be backed with some of the results presented in the next chapter, which show close to 50/50 participation from both right- and left-wing voters on these pages. General News more or less consists of all the most popular media outlets that are not considered tabloids such as DR the national public service news provider or *Berlingske*, a commercially driven news outlet that a few might consider politically biased, but generally embraced by a diverse cross-section of the Danish public.

The last data collection subset is the one that consists of public organizations such as NGOs, charities, government agencies and lobby organizations. No apparent categorizations schema could be found that was better than the generic one provided by Facebook, so it has been adopted here.

Topics

Being able to recognize patterns across various topics allows for a more precise mapping of the kinds of behaviour that is correlated with cross-cutting agreement. It is likely that topic of discussion is an important factor contributing to whether people agree or disagree about certain things. Whether a topic is politically pressing has a significant impact on people's engagement in relation to cross-cutting agreement (Gerber, Huber, Doherty & Dowling, 2012). Additionally, as was mentioned in chapter 3, the context to a particular discussion, including the topic, is a strong factor in determining participants' preferences for homogeneity vs. heterogeneity of groups and thus should be relevant for people's initial disposition towards either agreement or disagreement (Morey & Boukes, 2018). This study therefore takes the approach that cross-cutting agreement and disagreement are not evenly distributed across topics. Using a Big Data approach with high granularity can provide fairly accurate estimates of *how* much topics differ in terms of eliciting cross-cutting agreement or not.

The primary methodological challenge is how to categorize individual discussions, which entails developing a procedure for dividing discussions into groups based on their topic. Grimmer & Stewart (2013) provides a solid overview of the most typical approaches when dealing with text classification tasks. The validity and effectiveness of certain approaches are highly dependent on the main research objectives. Since this thesis relies on a Big Data approach, one requirement is that the classification procedure is automatable. Furthermore, the focus of this study is on how polarization patterns and cross-cutting agreement are distributed across different topics, rather than exploring which topics can be found or which are the most salient. For this reason, the approach of choice is *dictionary methods*, which are based on sets of words or n-grams that correspond to pre-selected categories (ibid., 8). Simply put, a word such as "dogfood" can be attributed to the topic "animals and pets", then depending on how many times the word "dogfood" appears in a text, the probability that the text revolves around the topic "animals and pets" can be calculated.

One of the advantages of dictionary methods is that they are very intuitive; there is a simple connection between a piece of text and its designated category. A disadvantage compared to methods such as machine learning based supervised classification or manual coding is that validating the effectiveness of the chosen categories becomes difficult. There is no straightforward way to estimate whether the words and phrases chosen to mirror a certain topic are the best ones. Furthermore, one of the most significant biases to be aware of when applying dictionary methods is when drawing upon lists of words and phrases used in previous studies as these are often highly context dependent with respect to the specific study for which they were developed (Loughran &

McDonald, 2011). For this reason, a list of words and their corresponding topics was developed specifically for this thesis.

The formula used to calculate which category a certain text falls under can vary depending on the purpose of the study (Grimmer & Stewart, 2013, 9). The first aspect to deal with is whether a discussion can only be labelled with one primary topic or is allowed to stretch across several topics. Intuitively the latter approach will appear to most adequately model the real world since actual communication practices rarely fit into neat categories such that all individual texts always pertain to only a single topic. It seems natural that some discussions may touch upon several topics, although there is still an advantage in being able to calculate the topic that is most strongly accentuated in a text. It might be relevant for discussions that loosely touch upon several topics, but still have one clear main topic to only count the main topic. In this thesis both approaches will be included. For summary statistics such as comparing distributions of polarization and cross-cutting agreement across different topics it is useful to only count each distinct discussion once, meaning a discussion can only fall into one topic. Restricting a discussion to only its primary topic will help sharpen the contrast between topics, rather than allowing discussion to span multiple topics, which would account for more complexity, but also make interpretations of the results more difficult. This requires a formula to determine which topic is most salient in any given discussion. In another case, where topics can be used as control variables when modelling the impact of features such as use of emojis, sex or language use, it can be a better approach to include all occurrences of topically charged words and then let the regression function sort out the relative import of each topic. The next section will go into further detail about topic choices and calculations.

Topic calculations and representations

For dictionary methods to work properly topics must be chosen from the outset and a list of words corresponding to each topic must be manually compiled using inputs from previous research, domain knowledge and exploration of the data. This project takes its main inspiration from the agenda setting literature where media coverage based on topicality has long been a focus area. Groshek & Groshek (2013) presents a list of 17 topics used to categorize news stories based on content, which will be used as the point of departure for choosing topics. However it will be updated to focus slightly more on political topics and be more applicable in a Danish context. Topics such as sports and culture are merged and so are the topics media and technology. The topics accidents and oddities are removed and instead the broad category politics is divided into foreign policy, social policy, domestic policy and refugees and integration. The complete list of topics and descriptions can be found in Appendix 7.0-SI. Finding all words and phrases that would best represent each of the topics requires a bit of manual work. Initial inspiration was sourced from the Danish media monitoring company Infomedia[23]. A combination of said list and the researcher's own knowledge of Danish news media and culture was used to compile a list of 2750 words corresponding to the chosen topics. As mentioned in the previous section, one of the disadvantages of dictionary methods is that it is difficult to validate the effectiveness of a specific dictionary, especially when it is applied to a huge dataset. However, because the dataset is large and since the main focus is on fairly broad trends, total precision with respect to matching words with topics is not an absolute requirement for the method to be useful. Still, one step of iterative correction was applied, which entailed picking 10 random Facebook posts labelled with a specific topic and then changing or removing words in the list if not all 10 posts were related to the topic. This process concluded in a final list of 2834 words corresponding to 16 topics including an additional topic named "other" for all posts that did not contain any of the keywords.

Following the usage logics presented above, a given discussion (a Facebook post) can be represented by the vector *x* where each element corresponds to the number of word occurrences that match one of the 17 chosen topics. Many posts might have multiple topics, but for the final analysis, it is useful to be able to reduce one Facebook post to a single topic. The list of words used to designate each topic is far from perfect. Some topics are by definition broader than others and some specific words used to designate them are likely to be more common. Thus, a method is needed to provide the best possible estimate for what is most likely the main topic of a given post. For this reason, the final score for each topic is given by the very popular TF-IDF formula (term frequency * inverse document frequency) (Řehůřek, 2011). This means that topics *and* words that are rarer

[23] https://infomedia.dk/blog/lyt-og-laer-kom-godt-i-gang-med-social-listening/. The list of words and corresponding topics used for consultation in the research design is no longer available at the provided link.

will be given a relatively higher value. For example, if a post contains one instance of a frequently occurring word and one instance of a fairly uncommon word, then the topic corresponding to the uncommon word will be given precedence, thus being labelled as the main topic for the post. Equation 7.0 shows the frequency value for a given word *t* based on the amount of times that word occurs across all posts *D*.

$$tf_i = \frac{tf_i}{T}(log_{\frac{d_i}{D}})^-1$$

Equation 7.0 TF-IDF formula.

The topic with the highest word count after the formula is applied to the word is labelled as the primary topic for a given post.

Harsh Language

As showed in the social analytics framework in chapter 4 sentiment or opinion mining is a central analytic piece when extracting knowledge from communicative behaviour on social media. Registering the overall tone in the great masses of texts available from such online spaces as social media platforms has caught the interests of especially marketers and political scientists in the last decade. Indeed, if writing on social media in relation to a specific product or public figure is notably positive or negative, it can be a powerful predictor of the public's actual, although simplified, opinion on any topic (Jungherr, 2015). The techniques associated with opinion mining have been heralded as a much cheaper and more effective tool for mapping public opinion compared to traditional survey approaches (Dalton, 2016). Though it should be mentioned that mining opinion from social media is often reduced to gauging whether feelings towards certain themes, ideas, products or people are positive or negative and can rarely be used to determine the complexities inherent in the opinions of individuals, especially in cases where the overall sentiment is both positive and negative. In the perspective of Big Data methods versus traditional quantitative approaches, an increase in volume, velocity and variety does come at the expense of specificity, peculiarity and depth. Social media-based opinion mining can cover more opinions, more topics and can be updated in near-real time without any additional costs, however it can be difficult to extract the opinions to very specifically formulated questions or explore the complexities of how people feel about certain issues.

The most popular term in the methodological literature is sentiment analysis (SA). It encapsulates the general approach of extracting sentiment from texts. As was mentioned in the previous section, there is a range of different approaches such as dictionary methods and supervised or unsupervised machine learning techniques, however at the time of writing supervised machine learning is by far the most researched approach for automatic sentiment analysis of texts from digital online media (Kumar & Jaiswal, 2019). One of the reasons for the popularity of this approach is its simplicity and flexibility with respect to how the automatic classification algorithm is trained. In a nutshell an algorithm is designed to simply recognize certain inputs such as examples of positively and negatively laden texts. One selection of texts is labelled as negative and another is labelled positive and then an algorithm is trained to best distinguish between the two selections until its accuracy can increase no further (Grus, 2015, 95). In contrast to the dictionary-based methods mentioned in the previous section, where a human agent is responsible for selecting words associated with a certain topic, this approach lets the machine figure out which words or combinations of words are most likely to cause a text to have a positive or negative tone, though the individual texts are still labelled by a human. The algorithm can easily be tweaked to specifically recognize texts that use violent or derogatory language instead of generic representations of negatively laden language, which is the background for one of the largest subfields of sentiment analysis, hate speech detection. Attempting to recognize texts that specifically contain hate speech, rather than just whether the tone is negative or positive, brings a lot of additional challenges with it because the context is much more sensitive to social and cultural issues (MacAveney et al., 2019). Furthermore, on the whole, supervised machine learning for general sentiment analysis and hate speech detection has become a huge research area, and what has, in this section, been presented as a very intuitive, simple and flexible method is by no means an easy thing to deploy. There are many technical intricacies pertaining to which statistical techniques are best used to optimize each individual algorithm, which is again dependent on the data used as input. Machine learning and artificial intelligence is only as good as the data used to train its underlying algorithms (Géron, 2017, 6). For this reason, the meticulousness of the human agents responsible for labelling the texts used to train the algorithm has a huge impact its effectiveness. This aspect is in many ways similar to issues in traditional content analysis techniques where the role of human coders is equally important. One key difference introduced by Big Data methods, which is especially relevant for supervised machine learning, is that "more trumps better" (Mayer-Schoenberger & Cuckier, 2013). There is a trade-off where a small increase in how accurately texts are labelled is less important than simply increasing the number of labelled texts.

In this thesis supervised machine learning is used to model harsh language use in Danish posts and comments on social media. The motivation behind tracing opinion sentiment is to be able to account for how people generally feel about certain topics or specific events. Because this project is aimed specifically at polarization and cross-cutting agreement it is of greater interest whether language is intentionally aggressive or not rather than the more generic dichotomy of negativity versus positivity. The original idea was to train a model that could recognize hateful speech, however such speech turned out to be fairly rare, only occurring in very specific situations. Instead the definition was changed to "harsh language" in order to be a bit less specific than the violent or threatening language aimed at minority groups, which are some of the characteristics often associated with hate speech. Harsh language is rather defined as instances of speech that is unnecessarily harsh to a degree where it is not productive for the debate. Using terms such as "idiot" or "clumsy clown" can be appropriate if used in the right context or to make a satirical point. In the same way, calling the prime minister an idiot compared to calling a fellow commenter an idiot can generally be regarded as less harsh. These cases were discussed with the coders, but the only formal definition was language as unnecessarily harsh.

Text Pre-processing

Being able to map harsh language in relation to political polarization and cross-cutting agreement requires the training of an algorithm that will be able to automatically evaluate the millions of Facebook posts and comments used as empirical data. As described in the previous section, supervised machine learning for sentiment analysis entails a selection of texts (posts and comments) to be first manually labelled by human coders as either containing or not containing harsh language and then used as inputs to train a statistical model. This section will describe the concrete steps necessary for obtaining a useful model. The main steps involve 1) coding posts and comments based on whether or not they contain harsh language, 2) transform the texts into a data format that is appropriate for formal statistical analysis, 3) train a model that is able to automatically recognize if a text contains harsh language or not. As briefly mentioned in the previous section, automatic sentiment analysis is a huge research area in its own right.

In the first step, three coders, all of whom were undergraduate students at the time, were recruited in addition to the author, for a total of four coders. After discussing the definition of harsh language (language that is unnecessarily harsh), 20,000 posts and comments were randomly selected and distributed among the coders. Texts were required to have a minimum length of 100 characters in order to make performance more reliable as very short texts will often contain too little information. This requirement pertains to both the coding process as well as the analysis meaning the final model is not applied to any text shorter than 100 characters, these will instead be labelled as null. Out of the 20.000 texts 538 were determined by the coder to be either non-sensical or too ambiguous for coding, 2.102 were labelled as harsh language and 17,360 were labelled as not harsh language. This comes to a fairly uneven distribution of labelled data samples since only a little less than 11% of texts contains harsh language, which provides some additional challenges when training the final model. In order to ensure the quality of the coded data, 150 texts were labelled by all four coders, which produced a Krippendorff's alpha of .81.

Since all statistical models are based on numerical inputs, a step must be taken to convert all texts into a format that is compatible with known mathematical structures. Simply put, strings of words need to become numbers. One of the most well-known approaches is known as the bag-of-words (sometimes called bag-of-ngrams) approach, where a text can be represented as an n-dimensional vector with each element corresponding to a certain word or combination of words to which the value represents the number of occurrences of that word in a specific text. If 1000 texts all together contains 10,000 distinct words, which is known as the vocabulary, then each of these texts can be represented by a vector with length 10.000 where element no. 3694 might correspond to the word "angry" and the value will designate the number of times that "angry" can be found in the text. All texts can then be represented by a m × n matrix (1000 × 10.000), though it goes without saying that it will be a sparse matrix containing many zeroes since a short text containing only 30 words still needs to be represented by a vector with length 10.000, even though most of the words in the full vocabulary have zero occurrences in the specific text.

The bag-of-words is used as the point of departure for converting texts to numerical representations. One of its main limitations is that the order of the words in a text is not accounted for. There are models such as those based on convolutional neural networks which are better able to account for the context around each word based on its preceding and succeeding words (Johnson & Zhang, 2015). However, since the techniques required for such approaches drastically increase the complexity of the model, the amount of labelled training data needs to increase in proportion for the model to actually perform better (Johnson & Zhang, 2016). Obtaining a huge amount of labelled texts is not feasible in this project, which is why text pre-processing is based on the bag-of-words approach, although a few techniques are used to optimize the usefulness of the numerical text representations beyond simply counting words. Three aspects are often addressed in bag-of-words approaches: 1) definitions of word-tokens, 2) calculating word importance, 3) word similarities.

When converting texts to structured data some cleaning steps are often necessary. Normally texts become tokenized and each word, separated by a whitespace, is regarded as a single token. If no cleaning is carried out these two tokens would not be identical: "awesome" and "awesome." because one of them ends with a period. A way to mitigate this is to simply remove all periods from the text before tokenizing it. Other choices have to do with whether to include words with spelling mistakes or non-sensical strings of letters. It can seem tempting to only include words found in an official dictionary, however sometimes, especially on social media, some words are repeatedly misspelled, and such behaviour can carry a lot of information with it (Řehůřek, 2011, 17). Some more advanced approaches include *stemming* and *lemmatization*. The former is the process of merging words that basically describe the same thing into identical tokens such that the words: "truck" and "trucks" become the same token. The latter describes the opposite process, that of separating words that appear similar but have different meanings depending on whether they are a noun or a verb such as “ferry” and “ferry”. Stemming and lemmatization require specialized, pre-programmed algorithms that are able to determine parts of speech (e.g. verb, noun etc.), which could not be found for Danish language in a reliable version. However, using a technique called word2vec, which will be described later, most of the benefits of stemming and lemmatization can be retained.

As mentioned, the basic version of the bag-of-words approach entails simply counting the occurrences of specific tokens in a text. However, some words have a tendency to occur much more often than others. Words such as “you” or “think” will often occur several times in the same text and thus many texts will demonstrate high values for such tokens even though common sense dictates that they are fairly neutral and unlikely to be important when identifying harsh language use. One of the most popular weighting schemes TF-IDF (term frequency * inverse document frequency), which was mentioned in the previous section, is an attempt to account for the relative importance of words across the entire corpus of texts (Řehůřek, 2011). Basically, words are assigned higher values if they are only found in a small handful of texts. Using this weighting scheme also increases one’s ability to determine the most important words for the classification task. In total the relatively small training data sample of roughly 20.000 texts contain a vocabulary of nearly 60.000 unique word-tokens. By including only words that appear at least 3 times the vocabulary size can be decreased to around 18.000. This is however still a large vocabulary and the computational power required to test many different models that all need to make millions of multiplications of these m × n matrices is still a little bit outside the resources available for this project. But, as mentioned earlier, it is common sense that some words are likely to be somewhat unimportant for classifying harsh language. By only selecting the word-tokens that have the highest values for each class (harsh language and not harsh language) compared to the rest of the classes. This means that if a maximum vocabulary of 5.000 words was enforced we would select the 2.500 words that have the highest proportion of the TF-IDF weighted values for texts labelled as harsh language, and vice versa for not harsh language. Selecting the final classification model will include testing different vocabulary sizes.

One last concern is addressed, which has to do with one of the inherent weaknesses in the bag-of-words approach. Words like “angry” and “furious” are semantically similar, but when used as tokens in numerical representations of texts they are treated as fully dissimilar words. It is common sense that some language patterns will become clearer if it is possible to account for the semantic similarities between words. A seminal paper from 2013 presented an effective solution to this issue, which is most often referred to as Word2Vec (Mikolov, Chen, Corrado & Dean, 2013). It is beyond the scope of this thesis to cover all the details of how Word2Vec models are calculated.

In brief, the intuition behind Word2Vec modelling is to take a huge corpus of texts, which in this case comes to approximately 2 million Facebook posts and more than 30 million comments written in Danish language. Based on how certain words are used together, i.e. appear near to each other in sentences or in specific sequences, word similarities can be extracted. The final Word2Vec model then contains n-length vectors representing every single word in the corpus where vector length depends on how much complexity should be retained in the representation of the word. Recommended length is 100-300 (Mikolov, Chen, Corrado & Dean, 2013, 7), to which a vector length of 250 was chosen for this project. The similarity between two words can then always be calculated using the distance between the vectors representing the two words[24].

A last synchronizing step is necessary before the Word2Vec model can be included in the final classifier to be trained to detect harsh language. The model is already based on a bag-of-words representation where each word-token corresponds to one element (a scalar) in an n-length vector. However, the Word2Vec model converts each word to a vector in its own right, thus, to get a meaningful representation of a single text, all word vectors should be transposed and averaged such that the full text can be represented by a 250-length vector. This process is called Doc2Vec (Kim, Seo, Cho & Kang, 2019). Using Doc2Vec provides increased flexibility meaning that a text can be represented purely by a 250-length vector of Word2Vec representations of words found in that text or this can be concatenated with the original n-length vector of TF-IDF weighted word counts. Tools used to create Word2Vec models have been adopted into the Python based library Gensim (Řehůřek, 2011), which is used in this project.

To summarize, the following choices were made as part of text pre-processing:

[24] There are many ways to calculate the distance between two n-length vectors. The distance between the cosine angle in vector space was used earlier in this thesis.

- All punctuation symbols were removed except when used together in cases where they form often used emojis (e.g. ": -)").
- All words were converted to lowercase.
- Misspellings and non-sensical strings of characters were not removed.
- Stemming and lemmatization were not applied.
- TF-IDF weighting schema was applied.
- A Word2Vec model was calculated and the per text averaged Doc2Vec was attached as a potential m × 250 feature to the text corpus.

Training the Algorithm

The training of supervised machine learning classifiers is a highly technical procedure where many different models and statistical techniques can be applied and tweaked in order to find the optimal algorithm. It is good to keep in mind that the purpose of this thesis is not to train the best harsh language detection algorithm, but rather to find the best possible one within the standard guidelines for model selection in supervised classification. One of the more typical approaches is to apply a degree of model agnosticism, which means that a few fixed versions of the input data are fed to a selection of the most popular classification models in order to see which one performs best when tasked with recognizing texts containing harsh language (Montiel et al., 2018). Most machine learning models have what is known as tuning parameters that determine aspects such as when the optimizer function should stop trying to converge. However, instead of trying to tune all these for a single model, it can be more effective to simply go with the default settings recommended by the developers of the models and then just test a variety of models while only tuning a one or two parameters.

The only model parameter (known as a hyperparameter in machine learning) to be considered is the regularization parameter. Regularization prevents weights from getting too high or low, which would cause some words to have disproportional impact on the evaluation. It is important in order to alleviate the risk of overfitting the model to the input data, which is a common problem with advanced machine learning techniques and complex, high-dimensional data. The model will simply become too good at recognizing patterns found in the input data, but when applied to new cases that might have a few additional, not previously seen patterns, the model performs badly. Simply put, based on the input value to the regularization parameter, the model prevents the values for the final parametrized model from becoming too high thereby making the model more robust (Géron, 2017, 27). In summary, the models to be tested will be different combinations of the following three aspects:

1. **Input data:** This involves the size of the vocabulary as well as whether or not to include the Word2Vec representations of the texts.
2. **Model type:** This involves which base algorithm to use (e.g. Logistic Regression, Random Forest Classifier, Multi Perceptron Neural Network etc.). The model type chosen is not of great concern since its performance and robustness is the only actual interest. The selection is made among a list of the most often used models in the machine learning literature, which is compiled by the developers of the SK-Learn library (Géron, 2017).
3. **Regularization Value:** A high, low and middle value is chosen as a potential regularization value for each model instance. This only applies to models that use regularization.

The final results of the performance testing can be found in Table 7.0[25]. All values reported are the macro means for the 10-fold cross-validation, which means that 10 permutations of the data trained and tested. The split between test and training data is 15%/85%.

As mentioned earlier, data samples are not evenly distributed between the two classes (harsh language and not harsh language), which is why the F1-metric should be used as the most important model selection criterion. Accuracy is important; however, the F1-score measures the balance between the number of true negatives and true positives, which is critical with uneven distributions. A model with an 80% accuracy but only true negatives and zero true positives is not a useful classifier. Fortunately, accuracy and F1-seems to go somewhat hand in hand. The best performing model appears to be a Multi-

[25] Only the top results are shown in the table. The full table can be found in Appendix 7.1-SI.

Layer Perceptron Neural Network using input data with a vocabulary of 7500 words, including the 250 features given by the Word2Vec model, and a L2 regularization penalty of 2.5.

Model Name	Accuracy	F1-Macro	Accuracy Std.	F1-Macro Std.	Run time
MLPClassifier_alpha=2.5_nwords=7500_word2vec_	0.8212	0.6987	0.0038	0.0099	0:20:53
MLPClassifier_alpha=5.8_nwords=7500_word2vec_	0.8256	0.6944	0.0054	0.0111	0:26:08
MLPClassifier_alpha=1.09_nwords=7500_word2vec_	0.8156	0.6935	0.0058	0.0118	0:11:48
LogisticRegression_C=1.09_nwords=7500_word2vec_	0.7986	0.684	0.0074	0.0074	15:02:29
LinearSVC_C=0.055_nwords=7500_word2vec_	0.8061	0.6812	0.006	0.01	0:39:36
LinearSVC_C=1.09_nwords=7500_word2vec_	0.7973	0.6797	0.006	0.0096	1:34:09
LogisticRegression_C=2.5_nwords=7500_word2vec_	0.7909	0.6789	0.0128	0.0172	1 day, 0:27:06
LinearSVC_C=2.5_nwords=7500_word2vec_	0.7967	0.6786	0.0056	0.0091	1:37:58
MLPClassifier_alpha=0.055_nwords=7500_word2vec_	0.8095	0.6784	0.0065	0.0102	0:11:57
LogisticRegression_C=0.055_nwords=7500_word2vec_	0.8162	0.6779	0.006	0.0098	0:01:44
LinearSVC_C=5.8_nwords=7500_word2vec_	0.795	0.677	0.006	0.0096	1:43:12
MLPClassifier_alpha=2.5_nwords=7500_	0.8122	0.6768	0.0089	0.0154	0:22:11
LogisticRegression_C=1.09_nwords=7500_	0.8045	0.6759	0.0084	0.0149	0:07:01
LogisticRegression_C=2.5_nwords=7500_	0.8037	0.6757	0.0083	0.0145	0:11:13

Table 7.0 Harsh language prediction models performance

The best model will be applied directly to all posts and comments in the final analysis in the next chapter. Since all models employ a so-called SoftMax function (Géron, 2017, 139) to determine if a piece of text contains harsh language, it is possible to extract a probabilistic measure instead of just the binary harsh language / not harsh language. This helps to account for some of the uncertainty in the model. Using the harsh language models in the final analysis entails summing over the likelihoods that a text contains harsh language. If a post has 20 comments where 19 are 0 % likely to contain harsh language and 1 comment is 50%, then that discussion has a total 5% probability of containing harsh language.

Chapter 8. Patterns of Political Homophily and Cross-cutting Agreement in the Danish Public on Facebook

Preparing analysis

The data preparation process described in the three previous chapters requires multiple analytic steps in order to organize all actors, posts, comments and interactions as well as the textual content of each message. It requires the parsing of hundreds of millions of data points. It is unfeasible to run the full data preparation process every time a single aspect is analysed. The data preparation requires one last technical step where all the data is batched and aggregated at a level that is suitable for performing flexible analysis.

The analysis is focused on how indicators of political polarization/de-polarization change over time, how they are distributed across spaces and topics and which characteristics of a discussion are most likely to push it towards either polarization or de-polarization. For this reason, all values can be aggregated at the level of a single post without losing critical information. However, because it can potentially be useful to look at which individual comments are most influential on the outcome of a discussion, some of these need to be retained. The data for the final analysis is split into three parts: 1) posts, 2) comments and 3) replies. The data structure is designed so that all three can be combined along both the first and second axis[26]. As an example, comments can be joined with the respective posts on which they originated, but they can also be analysed independently of the posts they belong to. This also means that all three parts will technically share the exact same variables, even though some variables will only be relevant for posts. Thus, for the final dataset every row can be considered either a post, comment or reply and each contains all the variables described in Appendix 8.0-SI. Each post, comment or reply contains a lot

[26] In SQL-language this corresponds to both union and join operations.

of variables, but these variables can roughly be divided into a number of categories. First, base variables contain the most rudimentary pieces of information such as the text of a message, the date and time, proportion of female and male participants, number of reactions and comments etc. Second, page category, which is just a single variable, provides information about the category that the page belongs to as they were conceived in chapter 7. Third, topic variables include the primary and secondary topics for a given discussion as well as the score for all topics pertaining to a given discussion as they were conceived in chapter 7. Fourth, political variables provide information about the voting intention of whoever writes the post/comment/reply, the proportion of left-wing or right-wing voters who participate, the proportion of voters for each party that participate and the political homogeneity, initial disagreement and subsequent agreement for a discussion. Fifth, sentiment variables contain information about the likelihood that a single post/comment/reply uses harsh language as well as the likelihood that the aggregated mass of comments made in a discussion contains harsh language. Sixth, meta variables are those that simply describe which database the original data was pulled from and the ID's of posts/comments/replies. The full list of variables with descriptions can be found in Appendix 8.0-SI.

The dataset prepared for the analysis represents the culmination of all methods pertaining to network attributes, topics and sentiment that were introduced in the three previous chapters. This dataset and the procedures for preparing it, which can be applied to any democratic multiparty system with a sufficient social media penetration represents one of the main accomplishments of this thesis project. It provides a very flexible way to analyse discussions on public Facebook pages from many perspectives, both in terms of broad trends and specific cases. The rest of this chapter will test and argue the usefulness of this dataset by analysing broad trends of political communication related to polarization and de-polarization in the Danish public.

Statistical modelling and inference

The purpose of this section is to give a general introduction to the statistical techniques that will be used with specific variables and cases to obtain the results that follow. Strictly speaking, the results reflect both an exploratory and confirmatory approach. A big part of this thesis is to develop computational Big Data methods for evaluating public opinion on social media. These methods, derived from a Big Data methodology, facilitate data that have many dimensions and high granularity. This gives the researcher many opportunities to dive deep into some aspects of the data and explore specific subsets. The purpose of the analysis is also to test a selection of relevant hypotheses as was laid out at the end of chapter 3 as these relate to some of the most pressing questions in social media research. However, the final dataset itself contains many prospects which will not be covered here.

Testing the hypotheses from chapter 3 roughly requires three types of analytic perspectives: 1) development over time, 2) distribution of activities across different topics and categories and 3) correlations between base variables and selected key variables related to polarization and cross-cutting agreement. In order to reject or verify the hypotheses it is necessary to confirm that any observed pattern is not a statistical artefact, but an indication of a real-world effect. For this reason, a rigorous statistical analysis procedure is employed, which is described in the following sections.

Bivariate relationships and contingency tables

Analysing development over time will be treated as a simple linear regression problem meaning that the average of any given key value will be modelled as a function of time. The recurring unit of time used in the results will be weekly increments. Preliminary exploration of the data seemed to suggest that looking at weekly development would be granular enough to reveal anomalies caused by significant real world events, but also containing a sufficient number of observations per unit that the timeline could be split across other dimensions (i.e. topics, pages) without the results becoming too unreliable. A common way to test the statistical significance of a simple linear regression is by looking at the t-ratio with respect to the principal coefficient, which is determined by the relation between the value of the coefficient and its standard error (Warner, 2008, 347). However, since a simple linear regression (containing only 1 independent variable) is not very computationally expensive, it is possible to do permutation testing instead, which is a slightly more exact method of evaluating the statistical significance of the relation between two variables (Anderson & Robinson, 2001). It provides more reliable results than t-ratio statistics because it is not built on the assumption that the underlying data has a perfect Gaussian distribution. Permutation tests involve testing all permutations of values in the actual distribution of the data rather than relying on the t-distribution. Thus, all those results in the following sections that are obtained by modelling the relationship between just two variables (bivariate regression) are subject to permutation tests for acquiring the statistical significance level.

The analysis requires the comparing of political polarization and de-polarization in terms of how they are distributed across different topics and spaces on Facebook. Comparing values between two or more groups is a common problem in statistics, most often tackled in medical science and referred to as contingency tables (Warner, 2008, 27). For this analysis it is necessary to compare the frequency of discussions (i.e. number of posts) in one category with that of another in order to infer whether independent categories are more likely to contain one type of discussion over another. In this thesis Fisher's exact test will be used to obtain the statistical significance that pertain to the difference of frequencies between groups. Originally designed to handle statistical inference for contingency tables that had either low frequencies or skewed distributions, Fisher's exact test can be used for almost all cases, though it becomes almost indistinguishable from Chi-Square Tests if samples are large enough (Warner, 2008, 325). Fisher's exact test is more computationally expensive than Chi-Square, but was chosen for thesis study as it is the most flexible. It was originally designed to handle 2x2 contingency tables, but the solution can be generalized to include N x M tables as well (Well & King, 1980).

Multivariate regression models

To fully understand how polarization and de-polarization effects are distributed across public Facebook pages and what the potential causes are, it is important to consider the multivariate effects of all available variables. It is needed in order to analyse the relationship between key variables such as political homogeneity and cross-cutting agreement and potentially related features such as harsh language use, emoji responses and gender distribution. Furthermore, it will also provide insights into whether there are overlapping or mitigating effects among all available variables. For example one particular media organization might appear to be posting a lot of content that promotes cross-cutting agreement, but they are actually just posting content within topics that are likely to cause cross-cutting agreement and it is in fact the topics, independently of the specific media outlet, which are the real predictors of cross-cutting agreement. The multivariate models greatly help avoid misinterpretations of results

One of the challenges of multivariate analyses is the complexity with which variables might affect one another. A popular approach to achieve estimates for positive and negative correlations between independent and dependent variable in a way that takes the interaction between parameters into account is structural equation modelling (SEM) and path analysis (Randall, 1992). However since SEM is more geared towards solving problems related to latent constructs of factor analyses in survey based research and not Big Data, it will not be applied in this analysis. SEM essentially consists of a set of techniques that can help social scientists select the best regression models and interpret potentially complex relations between predictors (Lin et al., 2017). Most of the same results can be obtained by making sure that the interaction effects between two or more predictors are taken into account and that appropriate measures for selecting the best model out of all possible configurations are taken. Additionally, SEM techniques are fairly specialized, not designed for Big Data, but rather the interpretation of survey data. General solution multivariate regression models provides more flexibility when working with large data sets.

The dependent and independent variables will vary based on the actual model being tested, but the model selection process will be the same for all models. Because models can be almost infinitely complex all regression models in this study will have both a simple and a complex version. The simple version will be fully linear and not consider the interaction between parameters on any level. The purpose of the simple model is to highlight which are the main predictors for any given dependent variable. For the simple model to be valid it is assumed that the complex model will show the same overall trend but add additional perspectives. The complex version will consider two types of non-linear effects: 1) interactions between parameters (i.e. infotainment * sad) with up to four levels of potential combinations (i.e. infotainment * sad * female * harsh language), and 2) higher order polynomial effects with a maximum power of four (i.e. sad^4). Interactions between polynomial effects will not be included. For the complex version any given model can easily end up containing tens of thousands of parameters, which is unlikely to be the best possible and most robust model. For this reason, model selection is extremely important.

Model selection

In this project the model selection process contains a number of steps, which apply to both simple and complex versions of all models. Because of the potential complexity of the models two different statistical techniques are employed to guide selection: 1) the variance inflation factor (VIF), which estimates collinearity between two or more values (Miles, 2014) and 2) Akaike Information Criterion (AIC) (Pan, 2001), which can be used to evaluate the parsimony of a given model. Collinearities of features in a model can make it difficult to interpret the contribution that one or two specific parameters provide. By estimating the VIF value for all potential independent variables it becomes possible to retain only variables that do not produce heavy collinearity. VIF is a ratio value meaning that a value of 20 can reliably be used as the maximum value that an independent variable can have without inflating the variance of the full set of parameters (Craney & Surles, 2002). AIC is a common indicator based on the log likelihood to help statisticians decide between two or more models. It penalizes models that have a bad ratio between number of parameters and log likelihood. For AIC the fixed values 4, 6 and 10 are the most commonly used to indicate whether one model is better than another (Dam, Heinesen & Wiltshire, 2017). Since this study is dealing with models that have large numbers of observations, 10 is used as the selection value. The process for the selection of multivariate regression models is as follows:

1. A data matrix is initialized so that values for all independent variables are pre-calculated, both linear and non-linear terms.
2. All independent variables are sorted by its Pearson correlation value with respect to the dependent variable from highest to lowest.
3. A full ordinary least squares model (OLS) containing all independent variables is produced in order to obtain the Variance Inflation Factor (VIF) for each independent variable.
4. All independent variables are now filtered based on the original sort in step 2 such that an independent variable is only added to the final list if it has a VIF score lower than 20, which would otherwise indicate fairly high collinearity with terms that have a stronger Pearson correlation.

5. The list of potential parameters from the independent variables obtained in step 4 is added one by one to an ordinary least squares model (OLS). If the Akaike Information Criterion (AIC) value is lower than 10, the parameter will be removed from the model again. Because not all permutations of parameters are evaluated against the AIC value of the model it is important that steps 2 – 4 ensure that the list of independent variables are sorted based on high Pearson correlation with low variance inflation. Independent variables are added to the model in the sequence that is most likely to incrementally increase the AIC of the model, though it can never be guaranteed that the absolute best model is found.
6. The final regression model is obtained when step 5 reaches the end of the list of parameters. For complex versions of a given model it is assumed that the majority of parameters will have been skipped.

For evaluating the final model after model selection, the following indicators are used: First is the R-squared value, which gives an indication of the amount of variance the model can explain with a value between 1 and 0 (Warner, 2008, 355). For example, if political homogeneity is the dependent variable and our model achieves an R-squared value of 0.99 it indicates that the independent variables in our parameterized model can almost perfectly explain the occurrence of politically homogenous discussions on Facebook. Second is the F-statistic which gives an indication of the statistical significance of the full model with respect to critical values of the F-distribution (Warner, 2008, 216). Third is the p-value that corresponds to a single parameter, which is calculated based on its t-value with respect to the critical values of the t-distribution when compared to the full model minus the respective parameter (Warner, 2008, 567). The p-value that corresponds to a single parameter is important because it indicates whether the underlying independent variable is a statistically significant contribution to the model.

Of course, exploring the results of the parametrized model entails using the estimated strength of the individual coefficients. If the use of Angry emojis are positively correlated with political homogeneity, then the coefficient corresponding to the number of Angry emojis used in a discussion should be a relatively strong positive number. The P-value can then be used to see whether the correlation is statistically significant. Because the models take unstandardized input variables, the initial values of the individual coefficients can be deceiving. In order to interpret the relative strength of individual coefficients, each must be normalized with respect to the mean value of the input variable. In the following analysis all figures that contain the results of regression models will have a corresponding table of normalized coefficients, which can be found in the appendices.

So far, this chapter has explained the general procedures, which help guarantee that the final analysis has a rigorous format. The rest of the chapter presents the results when the general procedures are applied to specific cases.

Political Homogeneity

This section seeks to address contemporary concerns about social media effects pertaining to whether curation logics are causing people to communicate increasingly with those who are politically similar, which can be considered a precursor to political polarization. As mentioned in chapter 3 previous findings on the subject are mixed showing both tendencies towards homogeneity and heterogeneity depending on the context and locus of the research.

This thesis is not claiming to present more precise or wholesome evidence about whether or not social media as such produce increased political homogeneity. The focus is on public pages on Facebook, which is only a small part of the role social media play. However, some gaps in the research are being addressed, namely the lack of connection between offline and online behaviour (e.g. Thomson & Wells, 2017) as well as the tendency for much research to be based on weak and overly specific concepts of polarization e.g. Republicans versus Democrats (e.g. Bail et al., 2018). These gaps are addressed by creating a politically meaningful measure of political affiliation that works both in bi- and multi-party systems and reflects offline voting behaviour as shown in chapters 6 and 5 respectively. Furthermore, this section will look into the development of political homogeneity over time rather than just a single case (e.g. Schmidt et al., 2017) or snapshots of selected periods (e.g. Bossetta et al., 2018). Such exploration is possible because political homogeneity is calculated on the message level (either a post, comment or reply) and is based on all users who participate by reacting to or commenting on the given message as was described in the "Reaching Agreement" section of chapter 6.

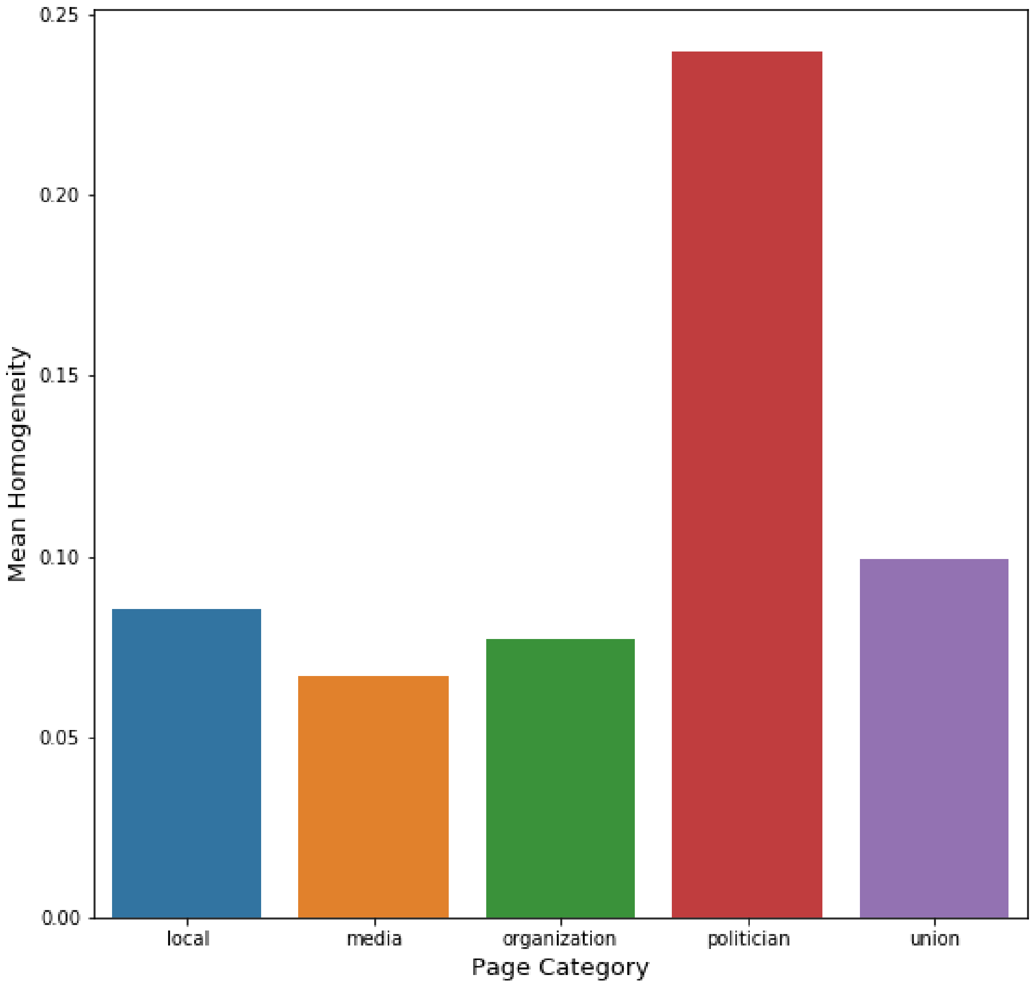

FIGURE 8.0 – MEAN POLITICAL HOMOGENEITY FOR EACH DATA COLLECTION

The main focus of this section is how levels of political homogeneity change over time and how homogeneity is distributed across spaces, topics and sentiment. Before going to the main results, it is helpful to have an idea about what to expect based on how political homogeneity is conceptualized and measured in this study. If we look at figure 8.0, we see that average political homogeneity is much higher for political pages than all other categories of page types. This is to be expected since all pages in this category will be directly affiliated with a specific political party for which many of them are primarily used for people to show their support. Further to be expected is pages that represent big organizations or top politicians have more activity and also a more diverse crowd of people. It is common sense that a current or former prime minister has a more politically diverse user base on their Facebook page compared to a much lesser known local politician, even though they both represent a specific political party. Table 8.0 shows the 25 pages with the highest average political homogeneity[27]. They are all local politicians and/or politicians who are generally known for having more extreme opinions.

TABLE 8.0 – MEAN POLITICAL HOMOGENEITY, TOP PAGES

PAGE_ORIGIN	HOMOGENITY_ALL
NYE BORGERLIGE I ASSENS	0,730607
NYE BORGERLIGE GREVE/SOLRØD	0,637899
NYE BORGERLIGE FAABORG-MIDTFYN OG ÆRØ KREDSEN	0,610913
NYE BORGERLIGE I HOLSTEBRO	0,584482
NYE BORGERLIGE FAVRSKOV	0,584392
PARTIET NYE BORGERLIGES VENNER I AABENRAA OMRÅDET	0,580085
BO ERIK HANSEN KANDIDAT FOR NYE BORGERLIGE NÆSTVED	0,56801
NYE BORGERLIGE SKANDERBORG-ODDER-SAMSØ	0,563877
NYE BORGERLIGE I LEJRE OG KØGE	0,560336
NYE BORGERLIGE SLAGELSE	0,548521
NYE BORGERLIGE VORDINGBORG	0,546922
NYE BORGERLIGE GULDBORGSUND	0,540424
NYE BORGERLIGE LOLLAND	0,539325
JAN KØPKE CHRISTENSEN, FT-KANDIDAT, NYE BORGERLIGE, LISTE D I SYDJYLLAND.	0,539115
NYE BORGERLIGE I AABENRAA KREDSEN	0,535288
NYE BORGERLIGE I HJØRRING	0,535169
NYE BORGERLIGE I RUDERSDAL	0,533303
NYE BORGERLIGE I ODSHERRED	0,523169
KRESTEN OLSEN NYE BORGERLIGE - GULDBORGSUND KOMMUNE	0,521055
NYE BORGERLIGE I NÆSTVED	0,521003

[27] Since the data collection contains nearly 10,000 unique pages. Only the top results are shown.

Pages with more activity would tend to have less political homogeneity in general, which is supported by a negative correlation between average activity and political homogeneity. While this is the general rule, it is by no means absolute. Figure 8.1 shows the relationship between average activity and political homogeneity for all pages except political pages[28]. The figure can direct us towards some of the outliers that defy the general trend. Most impressively we see two news media pages, Den Korte Avis and NewsPeek Network, which are well known outlets, especially popular with the Danish far right movement. Both have average levels of political homogeneity that are many times higher than the grand average while also having high levels of daily activity. A few less extreme but still significant outliers consist of a number of charity organizations such as Oxfam IBIS, Dansk Flygtningehjælp, Mellemfolkeligt Samvirke and Amnesty International Danmark. In contrast to the two previous examples, the charity pages all have user bases that are disproportionally slanted towards the political left.

[28] Political pages are omitted since they are generally expected to have very high levels of political homogeneity no matter what.

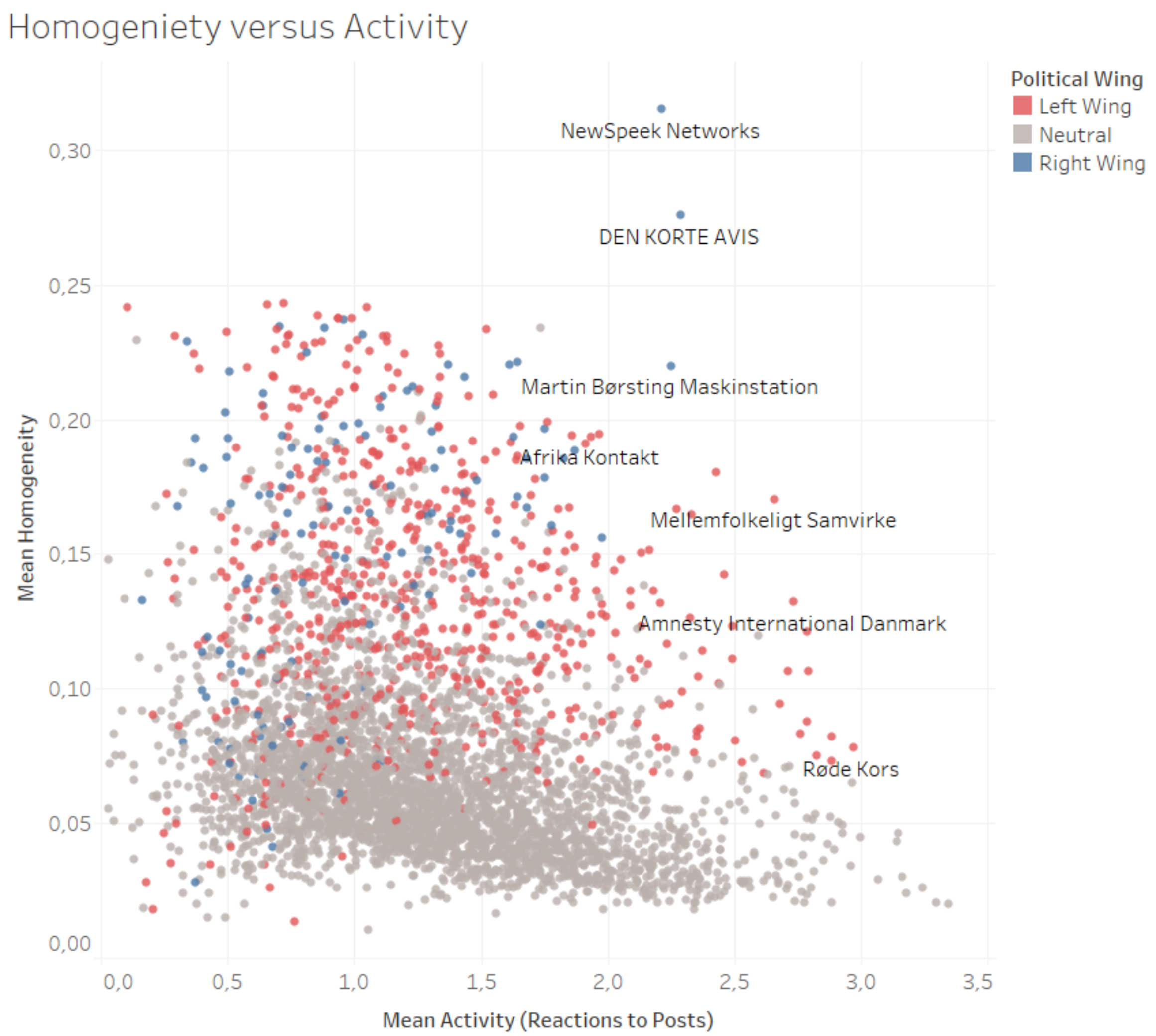

FIGURE 8.1 – SCATTERPLOT OF DISTRIBUTION OF GENERAL ACTIVITY AND MEAN POLITICAL HOMOGENEITY FOR ALL FACEBOOK PAGES.

Political Homogeneity Over Time

Looking at figure 8.2, which shows the average political homogeneity for all posts per week across all pages, topics and domains, we can detect a very slight increase in overall political homogeneity over the four years between 2014 and 2018. More noticeable is how much political homogeneity can fluctuate from week to week. The two spikes in average political homogeneity coincide with the national (2015) and regional (2017) elections of Denmark, which suggest that people are especially likely to seek out more similar views when political campaigns are active.

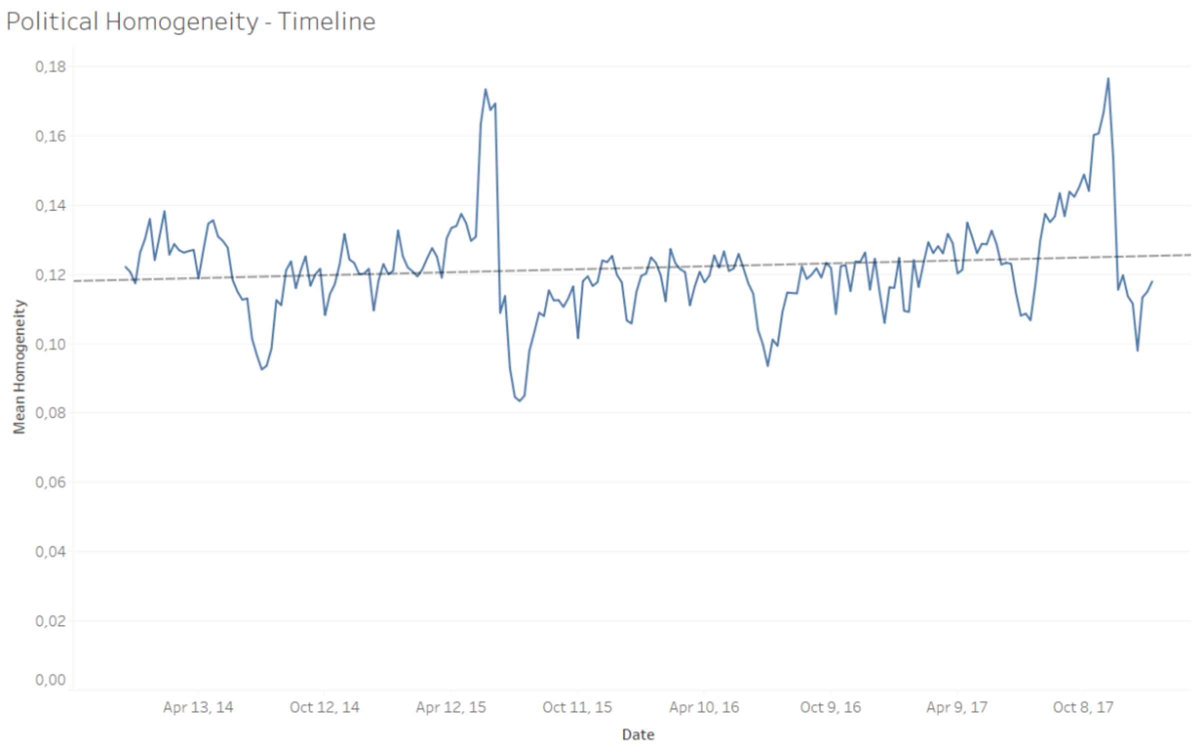

FIGURE 8.2 – MEAN POLITICAL HOMOGENEITY OVER TIME

Interestingly, if we split political homogeneity between reactions and comments, as shown in figure 8.3 we see that the overall increase seems to be caused by an increase in likeminded users who participate in discussion (comments) in contrast to those that simply react (reactions). While the effect is statistically significant to an acceptable degree ($p < .003$), the slope of the curve is so small that one should be cautious about concluding that a general rise in political homogeneity is occurring. The fact that political homogeneity fluctuates around a fairly stable average over several years attests to a small or non-existent long-time effect.

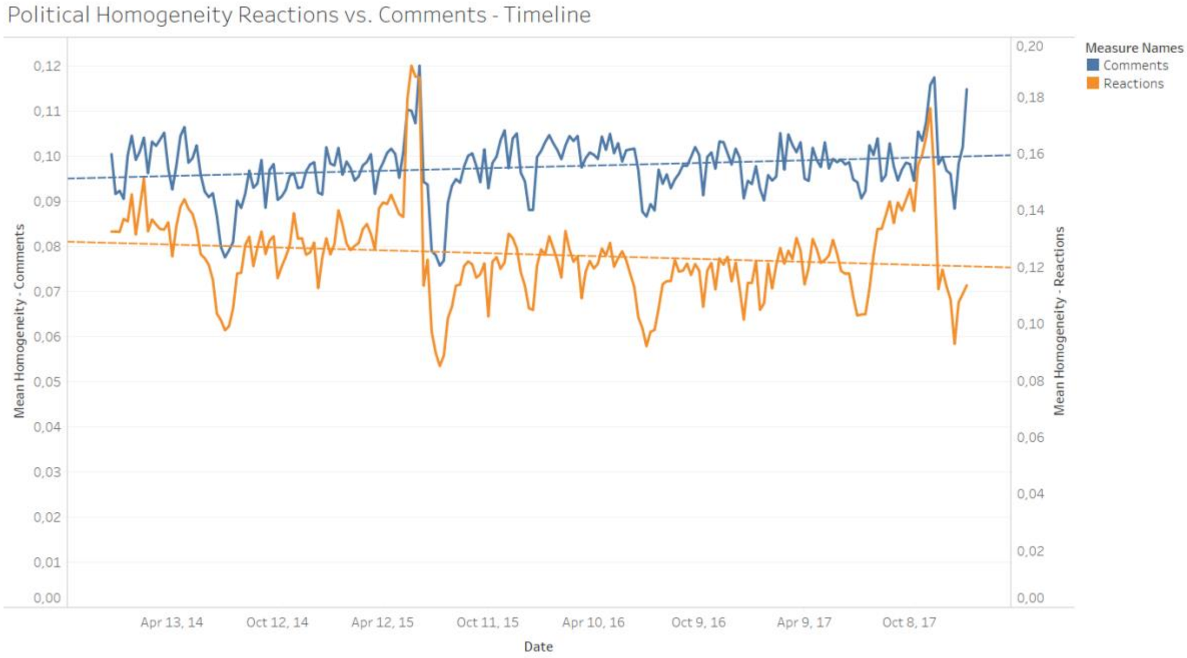

FIGURE 8.3 – MEAN POLITICAL HOMOGENEITY OVER TIME, REACTIONS AND COMMENTS.

What is more striking are the spikes that occur around the election campaigns. If the timelines are split between the different types of pages (politician, media, union, local, organization), as shown in figure 8.4, media and local pages are the main drivers of increases in homogeneity while the more overtly political spaces, pages belonging to politicians and unions, remain around average during the time of elections. This suggests that media and local communities are particularly good at curating content that is in line with people's political preferences during campaigns. It is also worth noting that media pages (4.8% increase, R2 = .201) and especially political pages (24.2% increase, R2 = .513) do see a rise in political homogeneity over the four-year period.

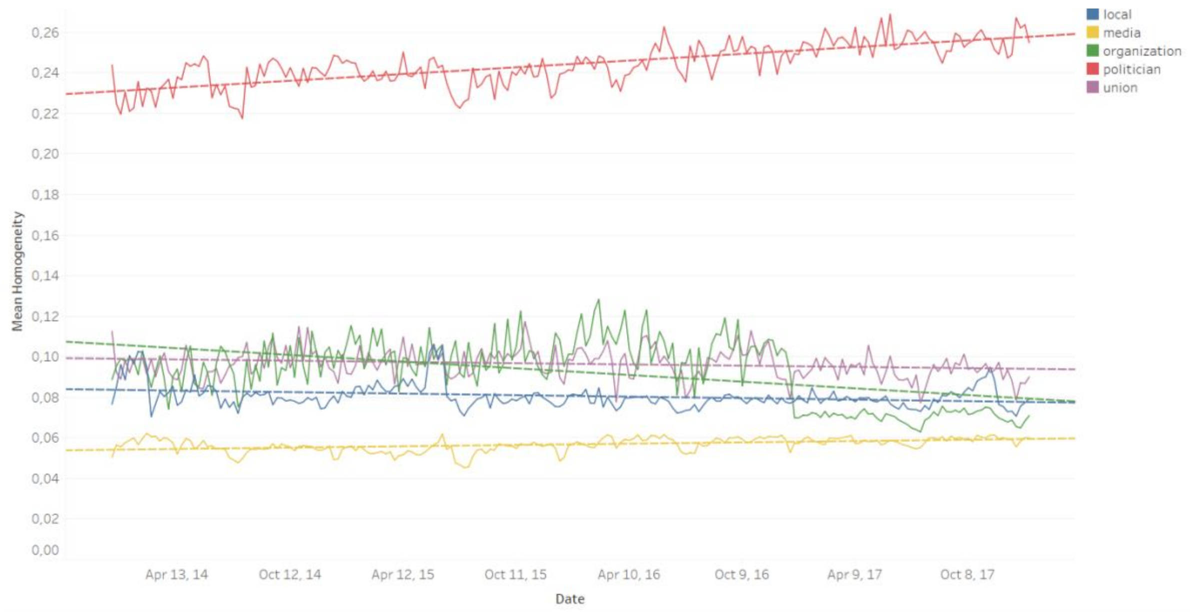

FIGURE 8.4 – MEAN POLITICAL HOMOGENEITY OVER TIME FOR EACH DATA COLLECTION

Topics and pages

It is expected that people are more attracted to some topics even if we don't agree with the message and vice versa. By looking at the increase of political homogeneity over time for each topic it is clear that increases, decreases or homeostasis are all trends depending on the topic, as shown in Table 8.1. Specifically, topics such as religion, refugees and immigration as well as justice and security are dominated by groups of users that are becoming increasingly homogenous between 2014 and 2018. For religion and immigration topics there seems to be a sharper increase in political homogeneity on political pages compared to those belonging to media organisations. In contrast, topics relating to the economy and the labour market have become much less homogenous both on political pages and media pages in the four-year period.

TABLE 8.1 – INCREASE IN MEAN POLITICAL HOMOGENEITY PER TOPIC

TOPIC	HOMOGENEITY OVER TIME - MEDIA	P-VALUE - MEDIA	HOMOGENEITY OVER TIME - POLITICAL	P-VALUE - POLITICAL

TECHNOLOGY AND DIGITA LIZATION	**2,45E-06**	**0,296015**	1,55E-05	< 0,0001
SOCIAL POLICY	**-1,88E-06**	**0,133203**	1,40E-05	< 0,0001
RELIGION	**2,50E-06**	**0,226175**	6,59E-05	< 0,0001
REFUGEES AND INTEGRAT ION	**6,79E-07**	**0,830634**	5,60E-05	< 0,0001
POLITICAL GAMES AND RE FERENDUMS	**-6,62E-06**	**0,000549 4**	5,01E-06	0,054145
JUSTICE AND SECURITY PO LICY	**6,49E-06**	**< 0,0001**	4,19E-05	< 0,0001
HEALTH	**1,95E-06**	**0,003601**	6,32E-06	0,061799
GENDER EQUALITY, GEND ER AND DISCRIMINATION	**-4,80E-06**	**0,069159 9**	2,06E-05	< 0,0001
FOREIGN POLICY	**1,52E-06**	**0,397795**	3,20E-05	< 0,0001
EVERYDAY LIFE AND CONS UMPTION	**5,57E-06**	**< 0,0001**	2,04E-05	< 0,0001
EMPLOYMENT AND THE L ABOR MARKET	**-1,53E-05**	**< 0,0001**	-1,40E-06	0,633151
EDUCATION AND RESEAR CH	**-6,22E-06**	**< 0,0001**	5,06E-06	0,09543
ECONOMY	**-5,35E-06**	**< 0,0001**	-1,58E-06	0,475989
DOMESTIC POLICY	**2,13E-06**	**0,032547 9**	5,14E-06	0,013226
CULTURE	**2,47E-06**	**0,000302 2**	1,13E-05	0,000511
CLIMATE AND ENVIRONM ENT	**-7,00E-06**	**0,000611 9**	3,63E-06	0,192386

It is worth noting that a topic such as religion has changed from being a topic with a lower-middle level of homogeneity to being within the top four passing both economy and labour market related topics, which have in turn fallen to much lower levels. This is illustrated in figure 8.5.

An examination of word usage strongly indicates that this increase in political homogeneity for the topic religion is entirely due to discussions about Islam and Islamic culture (see Appendix 8.1-SI). This is in line with the simultaneous increase in political homogeneity for content related to immigrants and refugees, who, in Denmark, are predominantly from Middle Eastern countries.

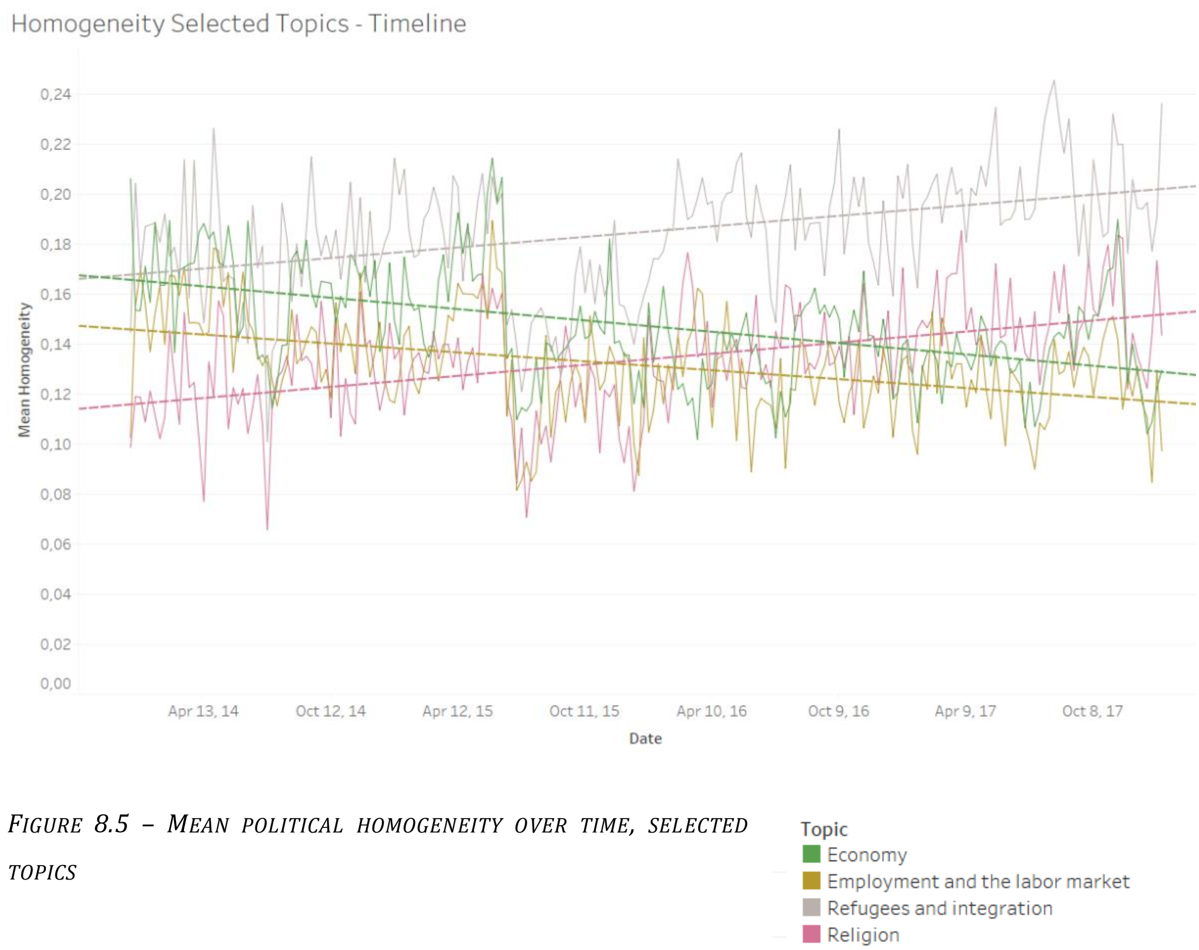

FIGURE 8.5 – MEAN POLITICAL HOMOGENEITY OVER TIME, SELECTED TOPICS

It is not surprising, albeit still an important finding, that topics related to immigration produce strong patterns of increasing political homogeneity. Immigration has become a hot-button issue in Europe over the last decade and the main cause of political division

(Holmes & Castañeda, 2016), which is likely making people averse to engaging with opposing views. Surprisingly, the results suggest that, as the locus of political division moves towards territorially external elements such as immigrants and foreign religions, people seem to simultaneously become more comfortable engaging across political lines when dealing with topics such as economy and the labour market, which have traditionally been more divisive areas.

Using the methods developed in this project, it is possible to zoom in further on specific areas of discussion. Table 8.2[29] shows the increase of political homogeneity within each page category for each of the types of pages: politician, media, local, union. There are few discernible results to note for local pages and unions. Over the last decade the independent unions have seen a surge in subscriptions and general interest, and it is possible that such a surge is related to the fact that other groups like FTF and AC are showing sharp increases in political homogeneity while independent unions remain unchanged. However, it is a bit speculative to suggest that union memberships are necessarily connected to political homogeneity on their respective Facebook pages. For local pages there is a small tendency for pages with high increases in political homogeneity to be from small and rural communes, though it is not an exclusive trend and it is difficult to infer something more without going into greater detail, which is beyond the scope of this thesis.

TABLE 8.2 – INCREASE IN HOMOGENEITY PER PAGE CATEGORY

PAGE CATEGORY	HOMOGENEITY INCREASE	P-VALUE
FAXE KOMMUNE	3,39E-05	0,000219
PARTY C	2,28E-05	0,00057
PARTY O	2,19E-05	< 0,0001
BRØNDBY KOMMUNE	1,81E-05	0,000199
TABLOID	1,31E-05	< 0,0001
GENERAL NEWS	7,11E-06	< 0,0001
PARTY AA	6,87E-06	0,044849

[29] Table 8.2 only shows the results for those categories that have a certain level of activity. At least 50.000 interactions over the whole period.

INFOTAINMENT	5,71E-06	< 0,0001
LIFESTYLE	4,89E-06	< 0,0001
SPORT	4,49E-06	< 0,0001
FTF	4,20E-06	0,213319
LEFT LEANING NEWS	2,96E-06	0,351757
PARTY F	1,74E-06	0,347609
PARTY A	1,44E-06	0,354863
PARTY I	3,43E-07	0,885231
PARTY B	-1,23E-06	0,66499
PARTY OE	-2,27E-06	0,0668
PARTY V	-5,67E-06	0,019844
LOCAL NEWS	-5,93E-06	< 0,0001
RIGHT LEANING NEWS	-1,20E-05	0,002562
FREDERIKSBERG KOMMUNE	-1,29E-05	0,496035
KØBENHAVN KOMMUNE	-1,35E-05	< 0,0001
CHARITY	-2,23E-05	0,35806
LO	-2,51E-05	0,000357
RINGKØBINGSKJERN KOMMUNE	-2,87E-05	0,03657
DEBATE	-3,49E-05	0,006617
ÆRØ KOMMUNE	-0,00026	0,474655

Political pages and media pages have more striking results. Populist parties such as Dansk Folkeparti (O) and Nye Borgerlige (NB) both demonstrate the highest levels as well as the largest increase in political homogeneity, which suggests that the rise of populism in Denmark, and Europe in general, is linked to the formation of spaces where such political factions increasingly homogenous and rarely challenged by diverse opinions. This trend is also potentially related to the tendency for populist and far-right parties to become gradually more extreme in their opinions, especially those that are fuelled by antiimmigration views. As an example, the party Nye Borgerlige (NB) was founded in 2014 and consists mostly of voters who thought that the older populist party Dansk Folkeparti (O) was too soft on immigration (Hvilsom, 2016)[30] and during the 2019 national election the party Stram Kurs, which is the most extreme-right wing party ever seen in Denmark, almost made it to parliament. In contrast, a far-left party such as Enhedslisten (OE) shows a sharp decrease in political homogeneity, which might be linked to them changing their stance on big political issues such as going from anti-EU to pro-EU[31].

For media pages it is worth noting that it the categories of General News and Tabloid which have seen the largest increase in political homogeneity, while partisan news media, both left and right wing, have remained more or less stable. Taking a peek inside the categories of Tabloid and General News, which consist of many of the most popular media outlets, users are becoming polarized across topical lines such that stories relating to immigration and religion are attracting an increasingly homogenous group of right-wingers whereas the same can be said about left-wingers for topics such as Gender Equality, Social Policy and Culture. This is illustrated in Table 8.3 where the variable *left-wing-increase* can be used to infer whether the increase in homogeneity is slanted towards the political right or left.

TABLE 8.3 – INCREASE IN HOMOGENEITY, MEDIA AND POLITICAL PAGES

PAGE CATEGORY	HOMOGENEITY INCREASE	HOMOGENEITY INCREASE - P-VALUE	LEFT-WING INCREASE	LEFT-WING INCREASE - P-VALUE
TABLOID	1,31E-05	< 0,0001	-3,35E-05	< 0,0001
SPORT	2,09E-06	0,001557	6,44E-06	0,030353
RIGHT LEANING NEWS	9,54E-07	0,774997	-1,01E-06	0,799477
POLITICAL NEWS	-2,74E-05	< 0,0001	-7,17E-05	< 0,0001
PARTY V	-3,66E-06	0,127804	1,60E-05	< 0,0001
PARTY OE	-3,20E-06	0,004348	-1,39E-05	< 0,0001

[30] https://politiken.dk/indland/art5637920/Nye-Borgerlige-giver-plads-til-h%C3%B8jreekstreme-danskere

[31] https://arbejderen.dk/idekamp/enhedslistens-holdningsskifte-til-eu

PARTY O	2,17E-05	< 0,0001		-1,11E-06	0,572741
PARTY NB	0,000135	< 0,0001		-4,48E-05	< 0,0001
PARTY I	-1,18E-06		0,47932	3,71E-05	< 0,0001
PARTY F	-7,71E-07		0,620307	-1,42E-05	< 0,0001
PARTY C	2,52E-05	< 0,0001		3,25E-06	0,363062
PARTY B	-5,53E-06		0,002281	-1,22E-05	0,062381
PARTY AA	-1,33E-06		0,549871	-2,66E-05	< 0,0001
PARTY A	1,74E-06		0,248246	7,84E-06	0,003509
LOCAL NEWS	-5,94E-06	< 0,0001		-4,07E-06	0,00977
LIFESTYLE	4,89E-06	< 0,0001		-2,05E-05	< 0,0001
LEFT LEANING NEWS	-4,78E-06		0,001606	-7,40E-06	0,001376
INFOTAINMENT	5,91E-06	< 0,0001		4,83E-06	0,129743
GENERAL NEWS	7,26E-06	< 0,0001		-2,18E-05	< 0,0001
DEBATE	3,81E-07		0,788666	2,96E-05	0,000166
CULTURE	-2,05E-05	< 0,0001		-3,01E-05	< 0,0001
CHARITY	6,61E-06		0,021265	4,66E-06	0,6821
BUSINESS	-6,74E-06		0,000745	2,30E-06	0,743746

At the same time, news media in the category Political News, which consists of all media organizations that brand themselves as focused on politics and generally not considered partisan, have seen one of the sharpest decreases in political homogeneity. This observation deserves some attention because it suggests that 1) people are not blatantly averse to seeking out spaces where they might encounter opposing political views, and 2) that some media outlets such as Tabloids, might be peddling stories that are politically appealing to specific political groups depending on the topics. An example would be stories about immigration that employ emotional language that appeal to the fears or grievances of narrow political segments thus increasing the political homogeneity on those posts. To really confirm this, a more in-depth discourse analysis would be needed. Another likely explanation for these results is that users who seek out political news sources are generally more politically engaged and feel confident defending their opinions to strangers with opposing views (Mutz, 2006), while users who engage with tabloid and general news outlets reflect less on their engagement with political news and are more interested in stories that they can initially relate to.

Becoming homogeneous

Political homogeneity is both increasing and decreasing depending on different situations, pages and topics on a wide selection of public Facebook pages. The purpose of this subsection is to address the issue of whether pages that are politically homogenous tend to attract more user activity over time. Examining the development of homophily over a fairly long stretch of time offers a robust indication of general patterns of political homophily on social media in general, especially compared to the previous studies mentioned in chapter 3 that mostly focus on a single point in time.

The rise of activity for individual pages over time is modelled as a function of both average political homogeneity and the gradual increase of homogeneity over time. This takes into account the fact that some pages are more politically homogenous than others as well as the potential for pages to become more or less homogenous as time goes by. This includes the possibility that some effects might be aligned with topics or page categories such as in the example with tabloid news in the previous subsection.

Two regression models are created, a simple one and a complex one that accounts for potential non-linear effects. Both are based on the independent variables: average homogeneity, increase in homogeneity over time and all topics as they were conceived in chapter 7. However, the model selection process can cause variables that do not contribute significantly to the explanatory power of the model to be filtered out. The dependent variable in this case is increase in activity over time, which is calculated as the slope for the average weekly increase in reactions, comments and shares to posts made by the page. Previous studies have found social investments by users on Facebook to differ depending on the type of interaction such that reactions are the least significant with comments being more of an investment and shares having the highest value (Winter, Brückner & Krämer, 2015; Kaur, Balakrishnan, Rana, Sinniah, 2018). Thus, the activity is calculated as *reactions+comments*1.5+shares*2.0* in order to account for the differences in perceived social investment. There are many small pages, especially among local community pages; and since each page will count as a single observation, pages that have very low weekly activity might produce unreliable averages, potentially skewing the results. Therefore, only the top 5% of pages in terms of weekly activity are selected.

Additionally, they must have at least 75% political penetration on average, which comes to a total of 691 pages.

FIGURE 8.6 – OLS RESULTS POPULARITY ~ HOMOGENEITY, SIMPLE

DEP. VARIABLE:	INCREASE IN ACTIVITY	R-SQUARED:	0.198	
MODEL:	OLS	Adj. R-squared:	0.193	
METHOD:	Least Squares	F-statistic:	39.29	
DATE:	Fri	11 Oct 2019	Prob (F-statistic):	1.06e-22
TIME:	03:45:17	Log-Likelihood:	684.04	
NO. OBSERVATIONS:	480	AIC:	-1360.	
DF RESIDUALS:	476	BIC:	-1343.	
DF MODEL:	3			
COVARIANCE TYPE:	nonrobust			
	coef	**std err**	**t**	**P>|t|**
CONST	0.0142	0.004	3.312	0.001
HOMO_INCREASE	-0.0092	0.001	-10.244	0.000
HOMOGENITY_ALL	0.1255	0.034	3.700	0.000
FOREIGN_POLICY	-0.3049	0.267	-1.141	0.254
OMNIBUS:	41.975	Durbin-Watson:	2.068	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	210.050	
SKEW:	-0.031	Prob(JB):	2.45e-46	
KURTOSIS:	6.240	Cond. No.	301.	

Looking at the results in figure 8.6 which is the simple regression model, we see that the only two statistically significant variables are average homogeneity and increase in homogeneity. Interestingly, increase in activity for pages is positively correlated with higher levels of average political homogeneity, but negatively correlated with an increase in homogeneity over time. The obvious implication here is that pages are more likely to keep people engaged when they have above average levels of political homogeneity, however a constant increase in homogeneity tends to discourage users on average. Having an appropriate amount of political homogeneity, but still be able to attract some diversity seems to be the most popular configuration over time.

FIGURE 8.7 – OLS RESULTS POPULARITY ~ HOMOGENEITY, COMPLEX

DEP. VARIABLE:	INCREASE IN ACTIVITY	R-SQUARED:	0.309	
MODEL:	OLS	Adj. R-squared:	0.299	
METHOD:	Least Squares	F-statistic:	30.14	
DATE:	Fri	11 Oct 2019	Prob (F-statistic):	1.93e-34
TIME:	03:43:51	Log-Likelihood:	719.61	
NO. OBSERVATIONS:	480	AIC:	-1423.	
DF RESIDUALS:	472	BIC:	-1390.	
DF MODEL:	7			
COVARIANCE TYPE:	nonrobust			
	coef	std err	t	P>|t|
CONST	0.0141	0.004	3.540	0.000
HOMO_INCREASE*ECONOMY	-0.0691	0.070	-0.985	0.325
HOMO_INCREASE*POLITICAL_GAMES_AND_REFERENDUMS	-0.2581	0.084	-3.064	0.002
HOMO_INCREASE	-0.0084	0.002	-5.563	0.000
RELIGION*EMPLOYMENT_AND_THE_LABOR_MARKET	49.5111	15.125	3.273	0.001
HOMOGENITY_ALL	0.0443	0.033	1.350	0.178
HOMO_INCREASE^3	6.908e-06	1.92e-06	3.591	0.000
TECHNOLOGY_AND_DIGITALIZATION^6	43.7132	464.451	0.094	0.925
OMNIBUS:	59.658	Durbin-Watson:	1.958	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	359.251	
SKEW:	0.299	Prob(JB):	9.76e-79	
KURTOSIS:	7.196	Cond. No.	3.53e+08	

The complex model shown in figure 8.7 suggests a few additional terms, the most interesting and only significant one being an increase in homogeneity to the power of three, which shows a positive correlation rather than a negative one. It generally becomes a bit speculative to attempt to interpret higher order polynomial effects, but it might help explain the fact that there is a minority of very popular pages that have both increasing homogeneity and activity.

It suggests that pages with a particularly large increase in political homogeneity are in fact more popular than the average page, which is in contrast to the more general effect where increase in homogeneity causes a drop in popularity. Looking at the top 20 pages where popularity has increased over the four-year period, it shows that 4 out of 5 of the pages with highest increase in homogeneity as well as an increase in activity are representatives of the populist movement in Denmark, namely Folkets Avis, Lokalavisen.dk, Den Korte Avis and Karen Jespersen who is the editor of Den Korte Avis. This is significant as it implies that the far-right populist movement in Denmark poses an exception to the rule that the most popular pages have a healthy mix of political homogeneity and some increase in diversity.

The complex model explains roughly 30% of the variance for pages that see an increase in activity over time, which indicates that political homogeneity, and in some cases increase in heterogeneity, contributes significantly to the popularity of discussion spaces on Facebook. It is important to remember that these are regression models that compare the increase of activity among the selected pages, which means that even though activity has in general increased on most pages since 2014, the results of the models implicitly take that into account. In order to account for a potential selection bias, a series of similar models were run selecting only media pages, only political pages or only local pages as well as pages that had lower levels of general activity, however all models showed the same overall results, only varying in the strength of the coefficients.

Homogeneity at the post level – anger and incivility

The final subsection will cover potential causes of political homogeneity at the level of individual posts. The main purpose is to investigate whether harsh language and anger facilitate higher levels of political homogeneity. It is theorised that users will stay away from spaces with opposing views or be discouraged to engage if the language and overall sentiment is very negative.

Anger and incivility are addressed by modelling political homogeneity at the post level as a function of emoji responses and harsh language. All base variables are included to act as controls. Since the dependent variable is average political homogeneity, it is sensible to exclude all variables that are naturally correlated with political homogeneity such as whether a post belongs to a political page or a left leaning media page. This allows for political homogeneity to be modelled more or less independently of which page it appears on. This is especially important when creating a model where the final values for the individual parameters are to be interpreted independently of the model in its entirety. Simply put, the predictive capacity of the model is not all that matters. It is important to be able to dissect the parametrized model and compare the effect of the key independent variables (harsh language and emojis) with the base variables.

The two normalized coefficients that are by far the strongest are harsh language and proportion of male participants, as shown in Figure 8.8. Emoji responses such as love and sadness are negatively correlated with political homogeneity, whereas angry emojis have a positive correlation. Having a high degree of angry men using harsh language is therefore likely to be the most homogenous discussions on public Facebook pages. It is in line with the theory that strong, negative feelings generally thrive better in a homogenous environment (Wollenbæk, Karlsen, Steen-Johnsen, Enjolras, 2019), although the fact that a greater percentage of men over women compounds the effect is more surprising.

*FIGURE 8.8 – OLS RESULTS HOMOGENEITY ~ *, SIMPLE*

DEP. VARIABLE:	**HOMOGENITY ALL**	**R-SQUARED:**	**0.264**	
MODEL:	OLS	Adj. R-squared:	0.264	
METHOD:	Least Squares	F-statistic:	3968.	
DATE:	Fri	22 Nov 2019	Prob (F-statistic):	0.00
TIME:	04:16:00	Log-Likelihood:	2.8687e+05	
NO. OBSERVATIONS:	253900	AIC:	-5.737e+05	
DF RESIDUALS:	253876	BIC:	-5.734e+05	
DF MODEL:	23			
COVARIANCE TYPE:	nonrobust			
	coef	**std err**	**t**	**P>|t|**
CONST	0.0997	0.004	22.833	0.000
REACTIONS_TOTAL	0.1354	0.001	126.407	0.000
WOMEN_ALL	-0.0723	0.001	-84.265	0.000
AGG_HATE_PROBABILITY	0.1481	0.002	94.446	0.000
REFUGEES_AND_INTEGRATION	0.1705	0.002	101.302	0.000
POLITICAL_GAMES_AND_REFERENDUMS	0.1992	0.004	54.273	0.000
RELIGION	0.0761	0.002	43.048	0.000
COMMENTS_TOTAL	-0.1229	0.004	-29.534	0.000
SAD_TOTAL	-0.1020	0.002	-51.862	0.000
ECONOMY	0.0753	0.002	30.789	0.000
JUSTICE_AND_SECURITY_POLICY	0.0509	0.002	26.712	0.000
TECHNOLOGY_AND_DIGITALIZATION	0.2508	0.003	71.744	0.000
ANGRY_TOTAL	0.0277	0.001	29.219	0.000

FOREIGN_POLICY	0.0527	0.004	14.743	0.000
HEALTH	0.0152	0.003	5.507	0.000
CLIMATE_AND_ENVIRONMENT	0.0464	0.004	12.649	0.000
DOMESTIC_POLICY	0.0211	0.002	9.804	0.000
LOVE_TOTAL	-0.0805	0.004	-18.058	0.000
EMPLOYMENT_AND_THE_LABOR_MARKET	0.0313	0.003	10.333	0.000
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	-0.0316	0.005	-5.867	0.000
SHARES	-4.919e-06	4.55e-07	-10.817	0.000
EVERYDAY_LIFE_AND_CONSUMPTION	0.0476	0.004	10.744	0.000
EDUCATION_AND_RESEARCH	0.0221	0.004	6.170	0.000
SOCIAL_POLICY	0.0541	0.003	18.047	0.000
OMNIBUS:	44630.650	Durbin-Watson:	1.862	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	96531.587	
SKEW:	1.035	Prob(JB):	0.00	
KURTOSIS:	5.200	Cond. No.	1.38e+04	

Less surprising is the presence of positive effects for topics related to immigration along with the Political Games and Referendums topic. The main reason for the latter topic is that it covers stories about poll results and are likely to have a headline such as "*candidate X is leading in the polls…*", which does not encourage much cross-cutting discussion. The fact that sad emojis have a negative correlation in the model suggests that stories that invoke sad emotions are more likely to encourage engagement from a wider political spectrum.

The complex version of the model (Appendix 8.8-SIADJ) is able to explain 35% percent more of the variance (R2 = .294) compared to the simple one (R2 = .193). It illustrates some of the same effects, though it becomes hard to interpret the cumulative effect of the higher order polynomials. We do see, unsurprisingly, that the two main coefficients from the simple model are dependent on other factors such as levels of activity and topics. For example, anger and harsh language is more likely to be associated with higher levels of political homogeneity when the discussion is centred on immigration compared to topics such as economy or domestic policy.

Political Disagreement and Cross-cutting Agreement

In the previous section polarization and de-polarization were considered a derived effect of political homogeneity or diversity. This section looks into cross-cutting agreement in relation to its potential for causing de-polarization in discussions that already have a certain level of political diversity. Cross-cutting agreement is slightly more complex than political homogeneity as it considers user interaction that is a result of both users' initial reactions to a post as well as their interaction in the comment section. The groundwork for this approach was laid in chapter 6 in the methods for calculating 1) *initial disagreement* represented by how politically charged users' reaction/comment patterns are, and 2) *subsequent agreement* represented by how many positive comment reactions are aimed at users who do have the same political stance as the commenter. As an attempt to simplify the analysis of cross-cutting agreement, this section seeks to flesh out a measure that represents a relation between initial disagreement and subsequent agreement. Simply put, initial disagreement and subsequent agreement needs to become a single value. Due to the complexity of analysing multiple steps of interaction, this section will first cover the measure of initial disagreement in isolation, and then in combination with subsequent agreement.

Initial disagreement in relation to political homogeneity

Initial disagreement should not be seen as a negative occurrence *per se* since having a certain level of political disagreement means there is at least a certain level of political diversity among the people who are disagreeing with each other. From how initial disagreement is calculated we can logically infer that discussion with low homogeneity does not entail high levels of disagreement necessarily; however, discussions with very high levels of homogeneity cannot produce high levels of initial disagreement since initial disagreement can only happen with at least some diversity. Discussions can have a diversity of participants, but not result in any political disagreement, whereas the opposite can never be the case. This means political disagreement is naturally negatively correlated with political homogeneity and when comparing the two it should generally be expected that if one goes up the other goes down or stays the same. It is important to keep in mind that low levels of initial disagreement do not necessarily guarantee agreeable content. Potentially divisive discourse might be found in spaces with high levels of homogeneity and never become exposed to people with opposing views and thus produce no political disagreement. It is furthermore important to reiterate that initial disagreement here is conceptualized as 'political disagreement', meaning that users can be disagreeing about other things that are not related to their observed political stances. Later sections in this chapter will look at cases where initial disagreement leads to subsequent agreement whereas this subsection will consider instances where initial disagreement is particularly high in order to highlight the main precursors of how users' initial responses are related to the measure initial disagreement.

Initial Disagreement Over Time

In Figure 8.9 we see how average initial disagreement fluctuates over time. The overall pattern is similar to that of political homogeneity, which consists of continuous fluctuations around a fairly stable average with some sudden spikes in value. It is worth mentioning that initial political disagreement is clearly more volatile, which suggests that some events are able to critically affect the amount of potential disagreement on Facebook.

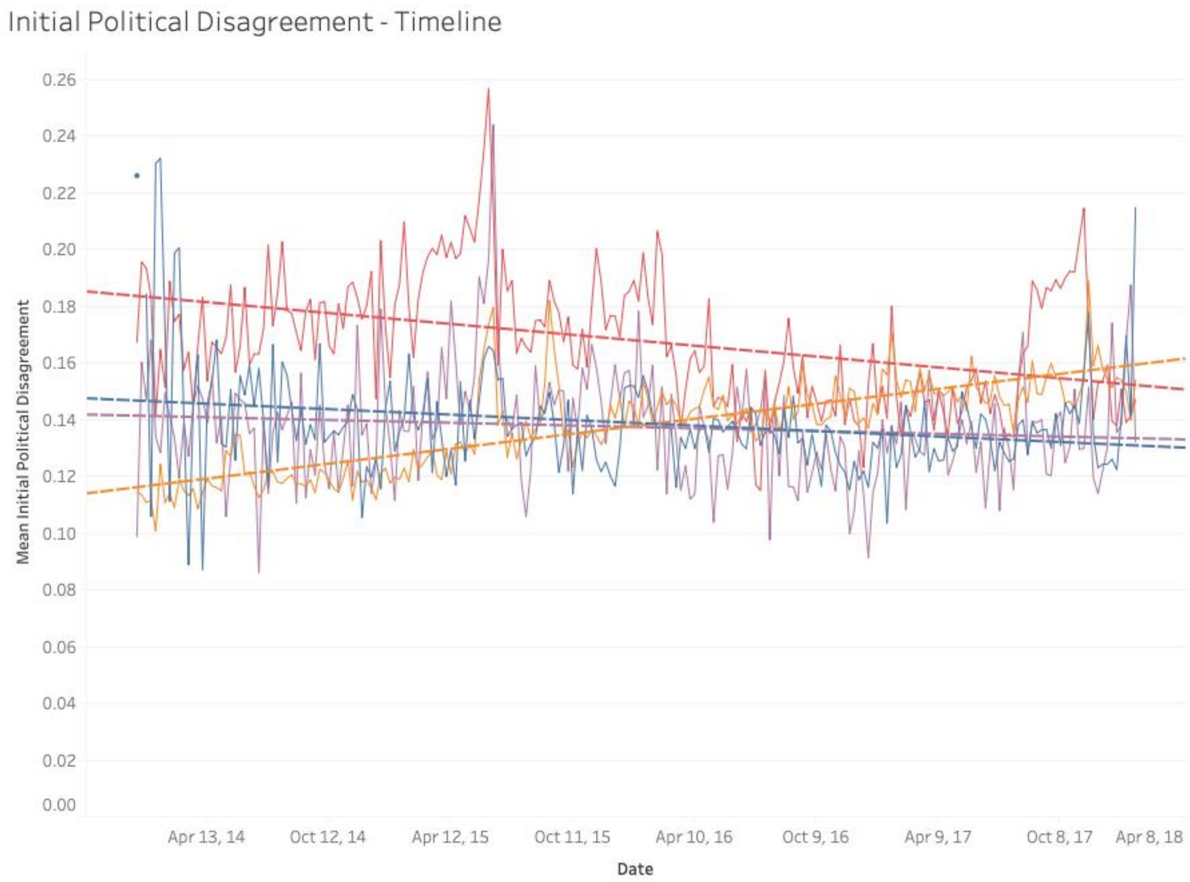

FIGURE 8.9 – MEAN INITIAL DISAGREEMENT OVER TIME PER DATA COLLECTION.

As expected, political pages which have seen an increase in political homogeneity show a decrease (R2 = .16) in political disagreement over the four-year period 2014 – 2018. There is a huge spike in initial disagreement on political pages right around the national election where, as seen in the last section, political homogeneity was just below average. Similar patterns occur during the 2017 local elections. This suggests that users do engage much more in cross-cutting discussion in political spaces around election time. Interestingly, public media pages elicit a different pattern. First off, a fairly significant increase in average initial disagreement can be observed, which runs somewhat counter to the expectations since homogeneity is also slightly increasing on media pages (see Figure 8.4 in the previous section). There is even a spike in initial disagreement around the 2015 election just as was observed with political homogeneity. Again, this goes against the logical expectation that average homogeneity should go down as initial disagreement increases since discussions with very homogenous collections of participants cannot achieve high levels of initial disagreement. The only way to explain why both values spike around the 2015 election is that both are caused by activity around more specific events such that initial disagreement increases on some pages, or even particular posts, while the same happens for homogeneity on different ones. This is supported by a significant increase in the standard deviation for initial disagreement as shown in figure 8.10. It is worth noting that the four-year increase in political disagreement on media pages is substantial enough that it actually overtakes that of political pages towards the end of 2017. This surely suggests media pages are taking up the role of an arena for cross-cutting discussion while political pages are in the process of becoming more of a space for political mobilization.

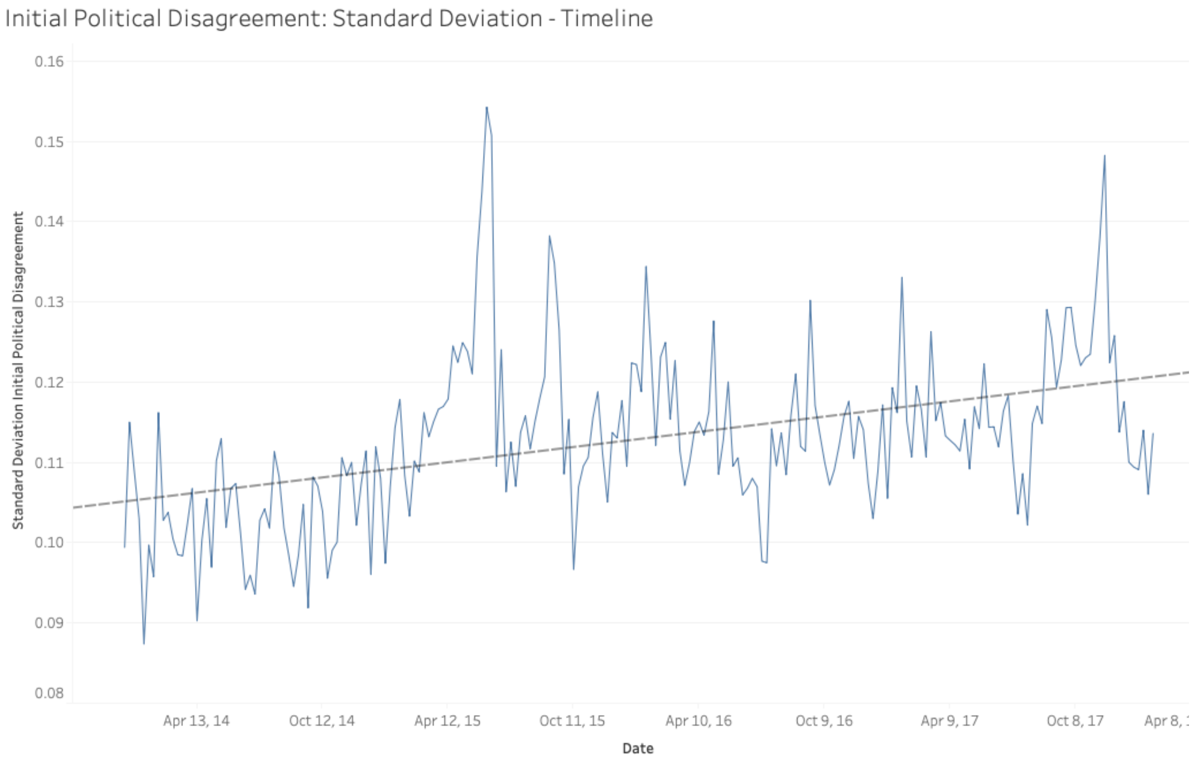

FIGURE 8.10 –STANDARD DEVIATION FOR INITIAL DISAGREEMENT OVER TIME.

On a week-by-week basis media pages elicit fewer volatile fluctuations in initial disagreement (Figure 8.9) compared to all other types of pages in general. This is most likely due to the fact that there is more activity to be found on media pages, which often causes a regression towards the mean. There are however four significant spikes to note, two of which happen around the national election in 2015 and local elections in 2017. The more significant of the two additional spikes happens around September 6th 2015 when a large caravan of refugees and migrants, who had been walking up through Europe, arrived at the Danish border, seeking passage to Sweden. This situation ignited a range of activities such as the Police temporarily detaining the caravan and citizens being arrested for trying to help the caravan by driving their members across the country in cars and buses. The fact that such a significant spike in initial disagreement happens around this time indicates that coverage of the issue swept across a very large cross section of media organizations in a way that also inspired many citizens with opposing political predispositions to engage in discussion. The most remarkable feature of this case is its rarity in terms of causing very high levels of initial disagreement on Facebook. It testifies to the fact that something singular and perhaps politically important takes place. Such an observation of event-based spikes in political disagreement across the entire public space on Facebook provides good arguments for social media publics as ad hoc publics of momentary connectedness that are none the less significant for public opinion formation. The case will be revisited later in this chapter.

The other spike in initial disagreement, which happens around January 29th, is a bit more difficult to grasp on the surface. Skimming over the top 100 posts that produce high levels of initial disagreement around the time, it seems the main focal point of discussion is the immigration policies of newly elected US president Donald Trump and French prime minister candidate Marine Le Pen. It is interesting that a politician like Donald Trump, who is overwhelmingly unpopular with the broader Danish population (Thobo-Carlsen, 2017), still produce opinions that strike a nerve with many Danes in a way that is potentially causing some degree of political division.

If we take a step back and look into the media page categories, it is clear that only some categories are the main drivers of increasing political disagreement. Media pages within the categories of Political News and Debate show the highest increase in disagreement, which aligns with the general expectation since both categories were also showing the most significant decreases in political homogeneity, as shown in the previous section. In contrast, the categories Tabloid and especially General News demonstrate increasing levels of political disagreement even though they also saw an increase in homogeneity. Zooming in further to look at how the increase is distributed among topics for all media outlets in the categories of General News and Tabloid, it shows that initial disagreement is increasing for all topics, though there are some that have increased more than others, specifically Refugees and Integration, Religion and Foreign Policy. At this point it becomes difficult to extract more definite patterns without looking at the content of some of the posts that generate high levels of initial disagreement. Table 8.4 displays key metrics for the top 25 posts with respect to initial disagreement for media pages within the mentioned categories and topics, and for comparison reasons Table 8.5 displays key metrics for the top 25 posts with respect to political homogeneity.

TABLE 8.4 –TOP 25 POSTS SORTED BY INITIAL DISAGREEMENT.

LINK TO MESSAGE	PAGE ORIGIN	MEAN HOMOGENEITY	MEAN INITIAL DISAGREE	LEFT WING COMMENTS	LEFT WING REACTIONS
HTTPS://WWW.FACEBOOK.COM/12860228293_10155233900013294	Politiken	0,139	0,862	0,377	0,888
HTTPS://WWW.FACEBOOK.COM/810040472452484_918504864939377	POINT of VIEW International	0,094	0,809	0,703	0,915
HTTPS://WWW.FACEBOOK.COM/168787544201_10154210174479202	Avisen.dk	0,02	0,774	0,012	0,985
HTTPS://WWW.FACEBOOK.COM/115104055206794_1440181959365657	DR Nyheder	0,04	0,765	0,585	0,784
HTTPS://WWW.FACEBOOK.COM/12860228293_10155848409428294	Politiken	0,023	0,742	0,355	0,893
HTTPS://WWW.FACEBOOK.COM/12787473132_10153204022628133	Berlingske	0,018	0,737	0,154	0,889
HTTPS://WWW.FACEBOOK.COM/12787473132_10153588665403133	Berlingske	0,026	0,734	0,696	0,264
HTTPS://WWW.FACEBOOK.COM/386305466118_10153577537426119	Ugebrevet A4	0,068	0,73	0,577	0,945
HTTPS://WWW.FACEBOOK.COM/810040472452484_1085572684899260	POINT of VIEW International	0,019	0,717	0,316	0,91
HTTPS://WWW.FACEBOOK.COM/12787473132_10154958140063133	Berlingske	0,013	0,69	0,29	0,766
HTTPS://WWW.FACEBOOK.COM/63503662682_10154524310422683	Jyllands-Posten	0,088	0,688	0,129	0,541
HTTPS://WWW.FACEBOOK.COM/12860228293_10156344982383294	Politiken	0,024	0,682	0,395	0,847
HTTPS://WWW.FACEBOOK.COM/63503662682_10153929912052683	Jyllands-Posten	0,056	0,68	0,194	0,64
HTTPS://WWW.FACEBOOK.COM/115104055206794_1271277509589437	DR Nyheder	0,022	0,679	0,227	0,81
HTTPS://WWW.FACEBOOK.COM/115104055206794_1293921317325056	DR Nyheder	0,031	0,678	0,418	0,899
HTTPS://WWW.FACEBOOK.COM/273409062862504_423985734471502	DR1	0,041	0,675	0,084	0,868
HTTPS://WWW.FACEBOOK.COM/12787473132_10155178531458133	Berlingske	0,049	0,675	0,18	0,678

HTTPS://WWW.FACEBOOK.COM/12787473132_10153881990373133	Berlingske	0,03	0,67	0,737	0,216
HTTPS://WWW.FACEBOOK.COM/38802765760_10153885493525761	P3 Nyheder	0,024	0,669	0,188	0,812
HTTPS://WWW.FACEBOOK.COM/810040472452484_1424685060988019	POINT of VIEW International	0,017	0,663	0,28	0,875
HTTPS://WWW.FACEBOOK.COM/63503662682_10153633667792683	Jyllands-Posten	0,063	0,663	0,624	0,138
HTTPS://WWW.FACEBOOK.COM/115104055206794_1191877674196088	DR Nyheder	0,037	0,662	0,593	0,684
HTTPS://WWW.FACEBOOK.COM/167016186701167_1038534406216003	Metroxpress	0,039	0,662	0,349	0,565
HTTPS://WWW.FACEBOOK.COM/12860228293_10155289033313294	Politiken	0,033	0,661	0,411	0,907

TABLE 8.5 –TOP 25 POSTS SORTED BY POLITICAL HOMOGENEITY.

LINK TO MESSAGE	PAGE ORIGIN	MEAN HOMOGENEITY	MEAN INITIAL DISAGREE	LEFT WING COMMENTS	LEFT WING REACTIONS
HTTPS://WWW.FACEBOOK.COM/106526434713_10154124967129714	TV 2 NEWS	0,383	0,091	0,057	0,019
HTTPS://WWW.FACEBOOK.COM/61055003519_10153540147413520	Ekstra Bladet	0,352	0,19	0	0,186
HTTPS://WWW.FACEBOOK.COM/115621461786836_1378527135496256	TV 2 NYHEDERNE	0,331	0,031	0,074	0,087
HTTPS://WWW.FACEBOOK.COM/106526434713_10154100958794714	TV 2 NEWS	0,301	0,064	0,096	0,13
HTTPS://WWW.FACEBOOK.COM/63503662682_10154117450497683	Jyllands-Posten	0,293	0,081	0,082	0,159
HTTPS://WWW.FACEBOOK.COM/106526434713_10153811804194714	TV 2 NEWS	0,289	0,168	0,05	0,202
HTTPS://WWW.FACEBOOK.COM/63503662682_10155225169417683	Jyllands-Posten	0,287	0,091	0,093	0,174
HTTPS://WWW.FACEBOOK.COM/12787473132_10152929071248133	Berlingske	0,286	0,097	0,137	0,077
HTTPS://WWW.FACEBOOK.COM/63503662682_10154981391867683	Jyllands-Posten	0,283	0,278	0,095	0,18
HTTPS://WWW.FACEBOOK.COM/12787473132_10154852122818133	Berlingske	0,281	0,104	0,129	0,143
HTTPS://WWW.FACEBOOK.COM/251133001593459_976380869068665	newsbreak.dk	0,28	0,197	0,235	0,095
HTTPS://WWW.FACEBOOK.COM/144493345745611_465211063673836	TV 2	0,28	0,088	0,004	0,209
HTTPS://WWW.FACEBOOK.COM/63503662682_10153803439907683	Jyllands-Posten	0,279	0,058	0,106	0,116
HTTPS://WWW.FACEBOOK.COM/251133001593459_933966679976751	newsbreak.dk	0,278	0,054	0,135	0,185
HTTPS://WWW.FACEBOOK.COM/251133001593459_1016379241735494	newsbreak.dk	0,277	0,072	0,166	0,112
HTTPS://WWW.FACEBOOK.COM/106526434713_10154121729224714	TV 2 NEWS	0,276	0,048	0,133	0,165
HTTPS://WWW.FACEBOOK.COM/12787473132_10152921147623133	Berlingske	0,275	0,194	0,155	0,051
HTTPS://WWW.FACEBOOK.COM/63503662682_10155209251467683	Jyllands-Posten	0,266	0,22	0,04	0,303
HTTPS://WWW.FACEBOOK.COM/251133001593459_988018514571567	newsbreak.dk	0,266	0,046	0,16	0,183
HTTPS://WWW.FACEBOOK.COM/115634401797120_1853428004684409	BT	0,262	0,331	0,16	0,169
HTTPS://WWW.FACEBOOK.COM/12787473132_10154991235428133	Berlingske	0,261	0,254	0,124	0,175
HTTPS://WWW.FACEBOOK.COM/106526434713_10153808059049714	TV 2 NEWS	0,26	0,094	0,171	0,114

HTTPS://WWW.FACEBOOK.COM/63503662682_10154388305137683	Jyllands-Posten	0,259	0,323	0,093	0,207
HTTPS://WWW.FACEBOOK.COM/106526434713_10155862535504714	TV 2 NEWS	0,259	0,101	0,089	0,217

The most striking feature about the content, without going into any deeper analysis, is that all posts with the highest levels of initial disagreement mostly contain very positive stories, especially those related to refugees, while posts with the highest levels of political homogeneity are more negative both in tone and content. Figure 8.11 extends to contain the top 100 posts with high levels of political disagreement and homogeneity, respectively. Each post is placed in a scatter plot that has percentage of left-wing voters who have reacted to the post (like, angry etc.) on the Y-axis, and percentage of left-wingers who commented on the X-axis. The figure displays an overwhelming tendency for high homogeneity posts to be caused by a high concentration of right-wingers while very few posts with high political homogeneity are caused by left-wing participants. Interestingly however, posts with high levels of initial disagreement are overwhelmingly determined by a fairly high degree of left-wingers who react, but an even higher degree of right-wingers who comment.

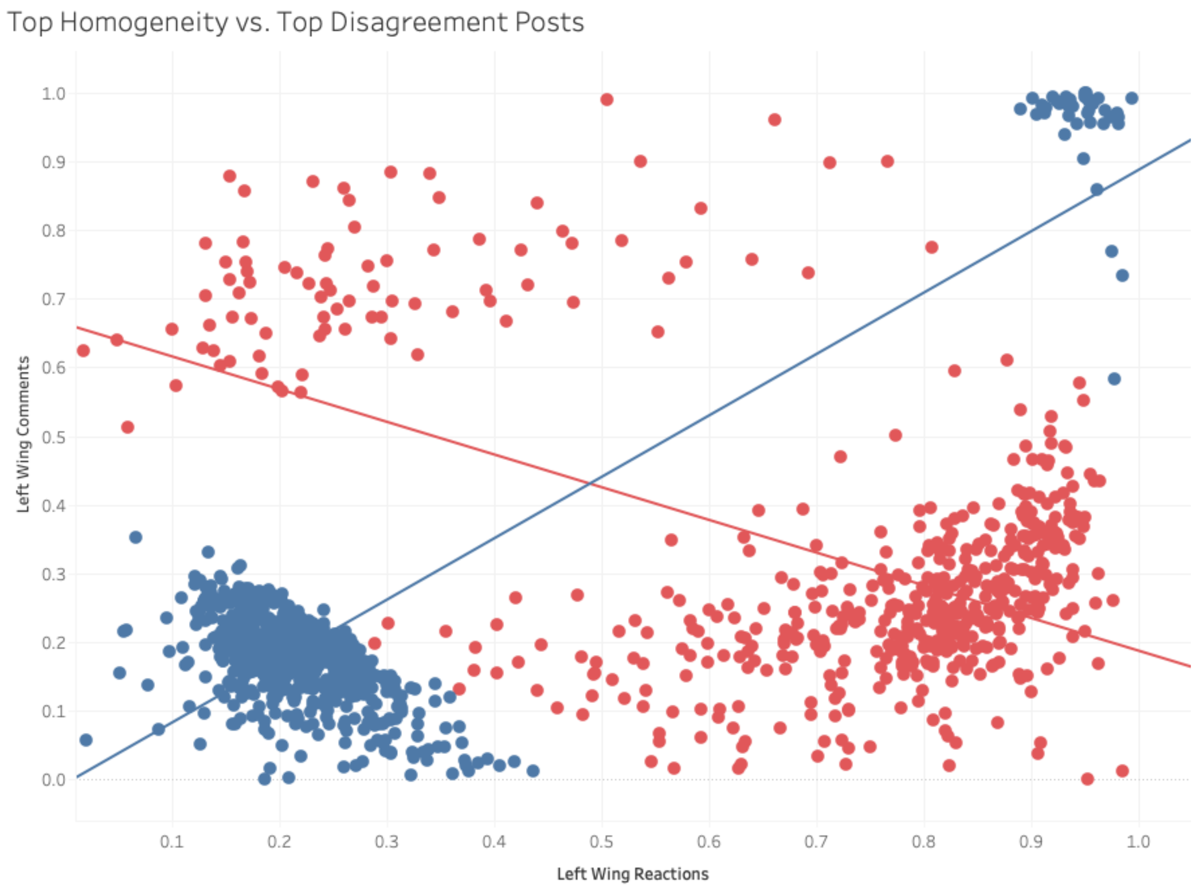

FIGURE 8.11 –SCATTERPLOT OF 100 TOP POSTS WITH RESPECT TO INITIAL DISAGREEMENT AND POLITICAL HOMOGENEITY

The findings in Table 8.4 and 8.5 as well as Figure 8.11 strongly indicate that public activity on General News and Tabloid media pages, when it comes to hot button topics such as immigration, refugees, religion and foreign policy, is determined by right-wing voters constantly challenging news pieces that are well liked by the political left while vice versa cases are rarely seen. Instead there is a much higher tendency for discussions to remain politically homogenous when they are dominated by right-wingers. With General News and Tabloid being the most popular of the media categories, this specific trend provides a solid explanation for why public media pages on Facebook are rising in both political disagreement and homogeneity. There may be other factors that contribute to the general trend and it is likely not possible to uncover them all without a much more in-depth qualitative approach, which the sheer number of posts and comments would make very difficult.

Like in the previous section it is considered whether an increase in initial disagreement is correlated with an increase in popularity for a given page. However, in this case there is no correlation, either negative or positive, to speak of.

Initial Disagreement at the Post Level – Love and Incivility

Following the analysis of political homogeneity this thesis wants to consider some of the general effects that contribute to initial disagreement on the post level. A simple regression model, which is able to explain around 23% of the variance, confirms that posts with high levels of initial disagreement share many of the same characteristics as those that have above average political homogeneity. As shown in figure 8.12, harsh language, overrepresentation of male participants and shorter discussions rather than longer ones are positively correlated with initial disagreement.

*FIGURE 8.12 – OLS RESULTS INITIAL DISAGREEMENT ~ *, SIMPLE*

DEP. VARIABLE:	**INITIAL_DISAGREE_ALL**	**R-SQUARED:**	**0.239**		
MODEL:	OLS	Adj. R-squared:	0.239		
METHOD:	Least Squares	F-statistic:	1157.		
DATE:	Wed	23 Oct 2019	Prob (F-statistic):	0.00	
TIME:	05:54:49	Log-Likelihood:	1.4357e+05		
NO. OBSERVATIONS:	169368	AIC:	-2.871e+05		
DF RESIDUALS:	169321	BIC:	-2.866e+05		
DF MODEL:	46				
COVARIANCE TYPE:	nonrobust				
	coef	std err	t	P>|t|	[0.025
CONST	0.6486	0.007	91.888	0.000	0.635
WOMEN_ALL	-0.0966	0.002	-58.167	0.000	-0.100
POLITICAL NEWS	0.0738	0.002	45.905	0.000	0.071
REFUGEES_AND_INTEGRATION	0.1599	0.003	54.957	0.000	0.154
TABLOID	-0.0296	0.001	-23.100	0.000	-0.032
HOMOGENITY_ALL	-0.7989	0.006	-138.727	0.000	-0.810

SAD_TOTAL	-0.1241	0.003	-35.514	0.000	-0.131
B	0.1041	0.002	59.485	0.000	0.101
LOVE_TOTAL	0.3717	0.007	50.977	0.000	0.357
COMMENTS_TOTAL	-0.3531	0.007	-49.213	0.000	-0.367
AGG_HATE_PROBABILITY	0.1202	0.003	44.442	0.000	0.115
JUSTICE_AND_SECURITY_POLICY	-0.1151	0.004	-32.845	0.000	-0.122
V	0.1024	0.002	58.236	0.000	0.099
HEALTH	-0.0845	0.005	-16.921	0.000	-0.094
ECONOMY	0.0418	0.004	10.914	0.000	0.034
ANGRY_TOTAL	-0.0206	0.002	-11.491	0.000	-0.024
POLITICAL_GAMES_AND_REFERENDUMS	0.0978	0.006	16.200	0.000	0.086
TECHNOLOGY_AND_DIGITALIZATION	-0.1097	0.007	-15.870	0.000	-0.123
LOCAL NEWS	-0.0074	0.001	-6.106	0.000	-0.010
LEFT LEANING NEWS	0.0401	0.002	19.400	0.000	0.036
F	0.1018	0.002	54.571	0.000	0.098
CULTURE	-0.0937	0.006	-15.513	0.000	-0.106
FTF	0.0135	0.003	4.402	0.000	0.008
SPORT	-0.0954	0.004	-25.084	0.000	-0.103
RELIGION	0.0277	0.003	8.769	0.000	0.022
LIFESTYLE	-0.0227	0.004	-5.772	0.000	-0.030
A	0.0859	0.002	55.535	0.000	0.083
NB	0.1553	0.005	33.013	0.000	0.146
I	0.0485	0.002	25.211	0.000	0.045
LEFT_WING_ALL	-0.0824	0.002	-38.699	0.000	-0.087
O	0.1312	0.002	56.145	0.000	0.127
CLIMATE_AND_ENVIRONMENT	0.0328	0.006	5.544	0.000	0.021
BRØNDBY KOMMUNE	-0.1118	0.008	-13.533	0.000	-0.128
EDUCATION_AND_RESEARCH	-0.0519	0.006	-8.579	0.000	-0.064
LO	-0.0006	0.003	-0.229	0.818	-0.006
C	0.0619	0.002	30.519	0.000	0.058
RANDERS KOMMUNE	-0.0607	0.010	-6.150	0.000	-0.080

AA	0.1047	0.002	47.819	0.000	0.100
OTHER	-0.0021	0.003	-0.843	0.399	-0.007
RIGHT LEANING NEWS	0.0338	0.002	18.334	0.000	0.030
SILKEBORG KOMMUNE	-0.0319	0.009	-3.599	0.000	-0.049
DEBATE	0.0019	0.002	1.029	0.304	-0.002
GENERAL NEWS	0.0019	0.001	2.064	0.039	9.54e-05
FREDERIKSBERG KOMMUNE	0.0909	0.004	23.129	0.000	0.083
HØRSHOLM KOMMUNE	-0.0610	0.019	-3.163	0.002	-0.099
OE	0.0763	0.002	40.492	0.000	0.073
BUSINESS	-0.0253	0.004	-6.417	0.000	-0.033
OMNIBUS:	25518.501	Durbin-Watson:	1.886		
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	42697.083		
SKEW:	1.013	Prob(JB):	0.00		
KURTOSIS:	4.395	Cond. No.	124.		

The topic Refugees and Integration is one of the top positive coefficients for initial disagreement. It is observed in the data that political disagreement favours an overrepresentation of right-wing voters over left-wingers. It can be a bit speculative to interpret exactly what this means, but it could be related to the previously observed trend of right-wingers often jumping into discussions to challenge messages that are supported by left-wingers. One of the main differences between modelling political homogeneity and initial disagreement is that love emojis are correlated with initial disagreement, whereas angry emojis were strongly correlated with political homogeneity. This feeds into the previously mentioned narrative that it is positive stories that are being challenged by the political opposition rather than negative ones.

A more complex regression model containing all the same independent base variables is able to explain 32% of the variance by considering that some of the effects might be non-linear (Appendix 8.12-SIC). Overall the simple and complex model show similar correlations, and it is not worth it to look too far into the details about how the two models might diverge since non-linear effects and the potential interaction between them are already difficult to interpret. The complex model here serves simply to establish how much of the variance in political agreement can be explained using the base variables. The important point to reiterate here is that there are a number of features that are correlated with both political homogeneity and initial political disagreement such as harsh language, overrepresentation of men and topics related to immigration.

Establishing cross-cutting agreement

The previous section specifically covered what in this thesis is conceptualized as initial disagreement (i.e. how users position themselves politically through their initial reactions to a post). Initial disagreement is when people with opposing voting intentions position themselves on either side of an issue, and as such at least some political heterogeneity is needed in order for initial disagreement to occur at all. Several noteworthy effects were pointed out in the previous section. Initial disagreement and political homogeneity on average being positively correlated with the same features such as harsh language, shorter discussions and overrepresentation of men while at the same time being independently, negatively correlated with each other. The most likely explanation for this observation is that only politically heterogeneous discussions that do not cause too much initial disagreement will exert inverted correlations. The prospect of users reaching agreement across political lines lies at the heart of political de-polarization. However, because of the wide range of social media pages included in this study, as well as the earlier mentioned notions that social media thrives on mixed content and blurred boundaries between public and private, it cannot be assumed that all posts have an equivalent political charge, even if they are published by media outlets that specialize in political news. Discussions that represent a politically heterogenous public with low levels of initial disagreement might simply entail that it is centred on a banal or uncontroversial issue. By using initial disagreement to estimate how politically charged a discussion is, the ensuing exchange of comments and replies provides a more reliable measure of cross-cutting agreement. In the following section it will be considered that even posts that start out with high levels of initial disagreement can move in different directions depending on the ensuing comments and interactions of the users.

In chapter 6 it was demonstrated how an estimate of subsequent agreement could be calculated from the comments and interactions that occur on a single post. If many users who are in political opposition are reacting positively to each other's comments, then subsequent agreement can be established. An important thing to note about subsequent political agreement is that it does not automatically distinguish between political and non-political content, which is also why this thesis will consider subsequent agreement in relation to initial disagreement for estimating real cross-cutting agreement. A quick way to illustrate the intuition behind subsequent agreement in isolation is with Table 8.6 that shows the top 10 media pages with the highest levels of subsequent agreement. They all belong to media organizations that focus heavily on sports and lifestyle related topics. Since the content is not politically charged users are not likely to be politically motivated in their engagement with content and other users and their individual actions are essentially random with respect to their political affiliation.

TABLE 8.6 – TOP 10 PAGES SORTED BY MEAN SUBSEQUENT AGREEMENT

PAGE ORIGIN	PAGE CATEGORY	MEAN SUBSEQUENT AGREEMENT
LIV	Lifestyle	0,3523
DR SPORTEN	Sport	0,3496
MIDTJYLLANDS AVIS	Local News	0,3486
CANAL 9 - SUPERLIGAENS HJEMMEBANE	Sport	0,3482
6'EREN	Sport	0,3461
DISCOVERY CHANNEL DANMARK	Infotainment	0,3454
MONTE CARLO PÅ DR3	Infotainment	0,345
BOLIGLIV	Lifestyle	0,344
TLC DANMARK	Infotainment	0,337
FIT LIVING	Lifestyle	0,337

Discussions should always be expected to exhibit fairly high levels of subsequent political agreement if the point of departure is not political. And as with initial disagreement, observing low levels of subsequent disagreement is not an argument that users are strongly at odds with each other since low levels can also be caused by the participants being very politically homogenous. To reiterate the main point, subsequent agreement is best understood in relation to initial disagreement, and the primary attention should be on posts that exhibit high levels of initial disagreement. By focusing on posts with high levels of initial disagreement we can generally expect that 1) the focal point of the discussion is political, which was illustrated in chapter 6, and 2) participants will have some political heterogeneity since initial disagreement cannot happen with a completely homogeneous crowd. Thus, on posts with high levels of initial political disagreement we can safely assume patterns of subsequent agreement to be non-random.

One productive approach to look further into patterns of subsequent political agreement and disagreement would be to disregard all posts that are below a certain threshold of initial disagreement. This threshold can be obtained from the results in chapter 6 using the distribution of posts labelled as political and non-political. A good point of departure would be the value of initial disagreement where 90% of the content is political. However, this approach entails filtering out a large amount of data and any statistical model would be less robust and generalizable as it would suffer from this filtering constraint. Instead it is possible to opt for an approach where the relationship between initial disagreement and subsequent agreement is put on a single dimension. This might retain a bit more noise but will be more inclusive of data overall. The objective is to cleanly separate posts with high levels of initial disagreement *and* high levels of subsequent agreement from those that have only lots of initial disagreement, but no subsequent agreement. In order to assure a useful transformation function that has empirical reliability, the results from chapter 6 are used to create a threshold value for initial disagreement to be used as a pivot. Considering all posts that that have a higher than 0.14 value for initial disagreement, it is possible to obtain a threshold value for subsequent agreement by taking the average subsequent agreement value for all posts that are above the initial disagreement threshold. The conditional function is illustrated in the table below (explanations for variables can be found in Appendix 8.0-SI); it serves the purpose of assigning low values to posts that are above the political disagreement threshold, but below the subsequent agree threshold and high values for posts that are above both thresholds while those that are below both are assigned middle values. The function ensures that a measure for cross-cutting agreement can be established using continuous rather than discrete values, and that the two thresholds serves as pivoting constants around which the values that reflect the relationship between initial disagreement and subsequent agreement are free to vary based on their original scores.

CROSS-CUTTING AGREEMENT CALCULATION	CONDITION

(INITIAL_DISAGREE_ALL*SUBSEQUENT_AGREE)*(1+ INITIAL_DISAGREE_ALL^2)	initial_disagree_all > 0.14 AND subsequent_agree => 0.26
(-INITIAL_DISAGREE_ALL*SUBSEQUENT_AGREE)*(1+ INITIAL_DISAGREE_ALL^2)	initial_disagree_all > 0.14 AND subsequent_agree < 0.26
-INITIAL_DISAGREE_ALL*SUBSEQUENT_AGREE	Matches none of the conditions above

With this function, posts (or comments) can be placed on a continuum that explains the degree to which users are able to reach agreement or not reach agreement as a result of interactions around the post. Again, it is values at the extremes that are the most interesting. The function is designed so that values around the average are likely to be those that have random or uninteresting effects with respect to political agreement/disagreement (i.e. non-political content or too politically homogenous to produce any disagreement/agreement). Values far above the average represent those discussions where users are able to reach some sort of agreement through cross-liking comments made by users with opposing political views, and very low values are those where users only like comments made by those that are politically similar to them. These effects will be referred to as *cross-cutting agreement* or *cross-cutting disagreement.*

Cross-cutting Agreement Over Time

Figure 8.13-A and Figure 8.13-B shows that the average change over time of cross-cutting agreement is very small, even smaller than that of political homogeneity and initial political disagreement (although there are some large fluctuations). Initially it could seem that the simultaneous rise of both political homogeneity and disagreement on media pages indicates some sort of political polarization process, which is an argument that can still be made regardless of how cross-cutting agreement effects are distributed. However, the fact that cross-cutting agreement is increasing slightly on media pages provides a counter narrative to that of political polarization.

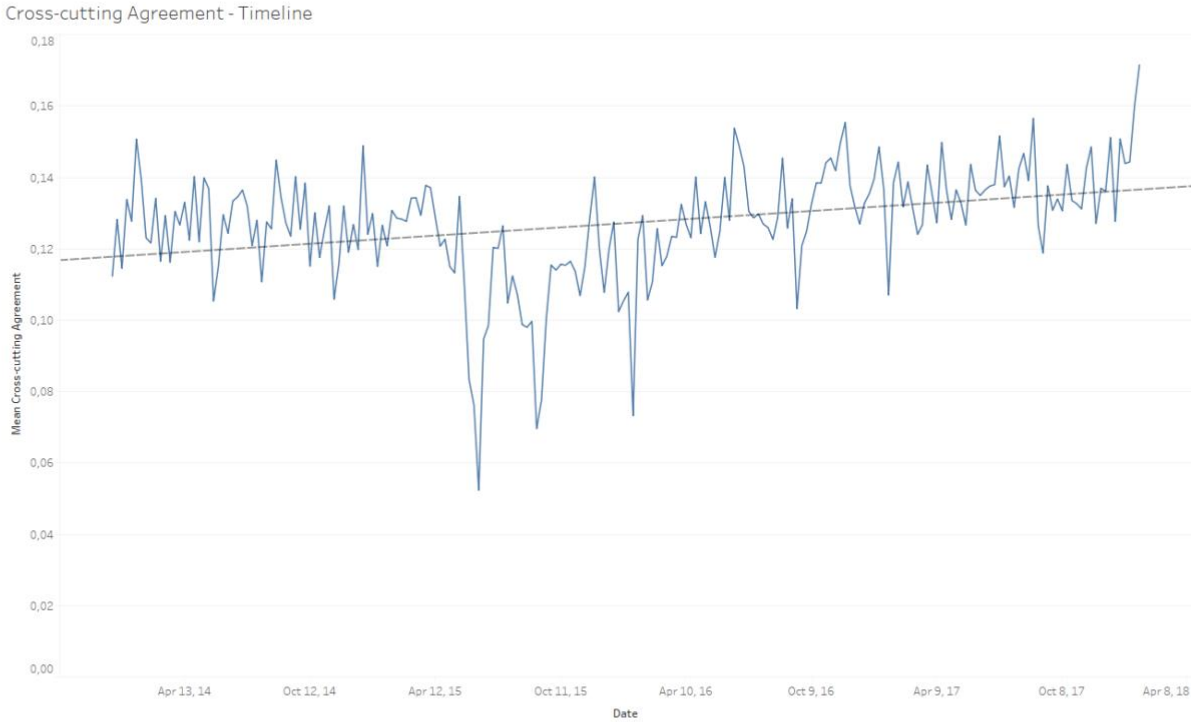

FIGURE 8.14-A – CROSS CUTTING AGREEMENT OVER TIME.

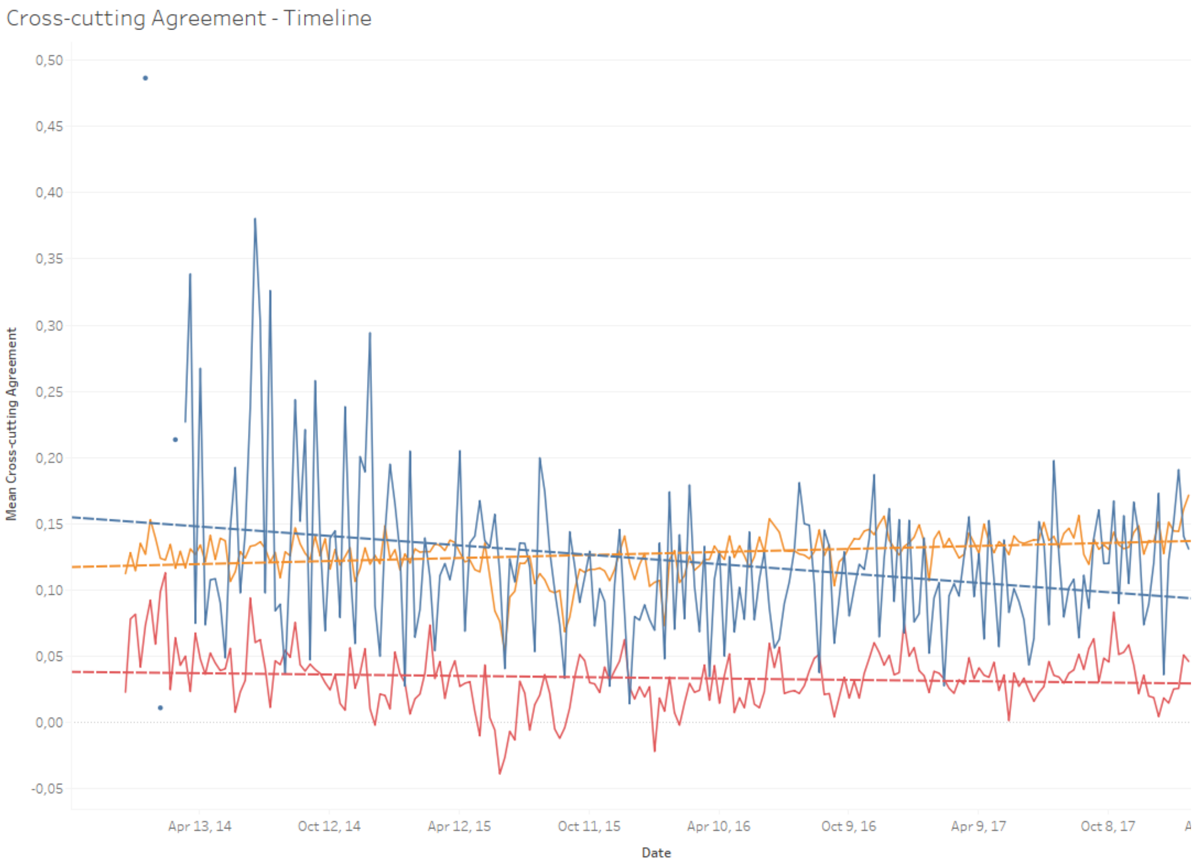

FIGURE 8.13-B – CROSS CUTTING AGREEMENT OVER TIME PER DATA COLLECTION.

The previous section demonstrated that mainstream news and tabloids were primarily responsible for the increase in initial disagreement. This increase appeared across all topics, though some were increasing more than others. With cross-cutting agreement it is possible to observe some much sharper trends, which are shown in Figure 8.14. Refugees and Integration and Religion are the only topics that show significant decreases of cross-cutting agreement. This finding is central because it adds further support to the notion that social media itself is not unilaterally fostering polarization, but rather that any such effects is contextually determined.

FIGURE 8.14 – CROSS CUTTING AGREEMENT OVER TIME PER TOPIC

TOPIC	SLOPE	P-VALUE
TECHNOLOGY AND DIGITALIZATION	8,74E-06	0,0539002
SOCIAL POLICY	1,35E-05	0,0037334
RELIGION	-7,34E-06	0,138646
REFUGEES AND INTEGRATION	-1,13E-05	0,0315973
POLITICAL GAMES AND REFERENDUMS	4,09E-05	< 0.0001
JUSTICE AND SECURITY POLICY	3,26E-07	0,889114
HEALTH	1,27E-05	< 0.0001

GENDER EQUALITY, GENDER AND DISCRIMINATION	3,56E-05	< 0.0001
FOREIGN POLICY	3,21E-05	< 0.0001
EVERYDAY LIFE AND CONSUMPTION	1,69E-05	0,001891
EMPLOYMENT AND THE LABOR MARKET	3,63E-05	< 0.0001
EDUCATION AND RESEARCH	2,21E-05	< 0.0001
ECONOMY	3,86E-05	< 0.0001
DOMESTIC POLICY	1,83E-05	< 0.0001
CULTURE	1,19E-05	0,0013372
CLIMATE AND ENVIRONMENT	2,37E-05	0,0073919

Looking at the cases from the previous section, both the week of the national election and the time around September 6th 2015 (the case of the migrant caravan), which had very high levels of initial disagreement and low levels of cross-cutting agreement. They are likely cases where the public is becoming politically polarized with not much agreement being reached through subsequent interactions among the users. In contrast the local elections of 2017 and the week around 29th of January, which also showed fairly high levels of initial disagreement, show comparatively much higher levels of cross-cutting agreement in subsequent discussions compared to the two other cases. The week around January 2017 included a lot of news stories featuring Donald Trump who is, as mentioned, widely unpopular in Denmark in general, which might explain how users are able to reach more agreement through subsequent interaction compared to the high levels of initial disagreement. In Table 8.7 and Table 8.8 we do see that the 20 posts that reach the most agreement compared to the 20 posts that reach the least agreement, the former has twice the number of Trump related stories. This is not definitive proof but does suggest that a topic such as Donald Trump makes it easy for Danish people to reach some agreement across political lines.

TABLE 8.7 – TOP 20 POSTS SORTED BY CROSS-CUTTING AGREEMENT (MOST AGREEMENT)

LINK TO MESSAGE	PAGE ORIGIN	DATETIME	CROSS-CUTTING AGREEMENT
HTTPS://WWW.FACEBOOK.COM/12787473132_10154302112523133	Berlingske	05/02/2017 21.49	0,952
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1840886912862829	Politiko	30/01/2017 17.43	0,939
HTTPS://WWW.FACEBOOK.COM/44741133186_10154934309178187	Altinget.dk	03/02/2017 08.27	0,932
HTTPS://WWW.FACEBOOK.COM/1430022983978849_1740135526300925	DR Politik	30/01/2017 19.58	0,906
HTTPS://WWW.FACEBOOK.COM/12860228293_10155726293388294	Politiken	28/01/2017 07.20	0,904
HTTPS://WWW.FACEBOOK.COM/12787473132_10154294377003133	Berlingske	02/02/2017 20.20	0,895
HTTPS://WWW.FACEBOOK.COM/12787473132_10154300569328133	Berlingske	05/02/2017 07.12	0,89
HTTPS://WWW.FACEBOOK.COM/63503662682_10154395717037683	Jyllands-Posten	30/01/2017 10.17	0,877
HTTPS://WWW.FACEBOOK.COM/199017183441852_1563449143665309	DR P4 Nordjylland	02/02/2017 20.05	0,859
HTTPS://WWW.FACEBOOK.COM/115104055206794_1437877716262748	DR Nyheder	04/02/2017 09.15	0,856
HTTPS://WWW.FACEBOOK.COM/606089332774857_1390896030960846	DR K	30/01/2017 12.35	0,854
HTTPS://WWW.FACEBOOK.COM/115104055206794_1429061637144356	DR Nyheder	27/01/2017 11.52	0,829
HTTPS://WWW.FACEBOOK.COM/115104055206794_1431818863535300	DR Nyheder	30/01/2017 07.19	0,828
HTTPS://WWW.FACEBOOK.COM/34290022401_10154987443612402	Kristeligt Dagblad	03/02/2017 14.00	0,823
HTTPS://WWW.FACEBOOK.COM/240993322627954_1307931532600789	RANDERSiDAG.dk	30/01/2017 09.49	0,816
HTTPS://WWW.FACEBOOK.COM/284523758316077_1003610976407348	DR P4 Østjylland	01/02/2017 21.32	0,812
HTTPS://WWW.FACEBOOK.COM/12787473132_10154286266313133	Berlingske	30/01/2017 18.08	0,806
HTTPS://WWW.FACEBOOK.COM/115104055206794_1436921646358355	DR Nyheder	03/02/2017 12.28	0,803
HTTPS://WWW.FACEBOOK.COM/12787473132_10154283171388133	Berlingske	29/01/2017 10.15	0,797
HTTPS://WWW.FACEBOOK.COM/106526434713_10155158826639714	TV 2 NEWS	31/01/2017 06.09	0,79

TABLE 8.8 – BOTTOM 20 POSTS SORTED BY CROSS-CUTTING AGREEMENT (LEAST AGREEMENT)

LINK TO MESSAGE	PAGE ORIGIN	DATETIME	CROSS-CUTTING AGREEMENT
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1842571599361027	Politiko	02/02/2017 20.19	-0,513
HTTPS://WWW.FACEBOOK.COM/810040472452484_1085572684899260	POINT of VIEW International	02/02/2017 15.37	-0,506
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1842393666045487	Politiko	02/02/2017 13.18	-0,503
HTTPS://WWW.FACEBOOK.COM/12787473132_10154285449953133	Berlingske	30/01/2017 09.45	-0,488
HTTPS://WWW.FACEBOOK.COM/124807067697288_695614357283220	DR2	28/01/2017 15.43	-0,487
HTTPS://WWW.FACEBOOK.COM/12860228293_10155750679898294	Politiken	04/02/2017 18.43	-0,481
HTTPS://WWW.FACEBOOK.COM/1430022983978849_1741771812803963	DR Politik	02/02/2017 19.59	-0,439
HTTPS://WWW.FACEBOOK.COM/12860228293_10155749567788294	Politiken	04/02/2017 10.48	-0,438
HTTPS://WWW.FACEBOOK.COM/115634401797120_1713065668720644	BT	29/01/2017 10.00	-0,431
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1840704256214428	Politiko	30/01/2017 09.45	-0,419
HTTPS://WWW.FACEBOOK.COM/136386436372451_1460401573970924	TV 2/FYN	01/02/2017 12.54	-0,406
HTTPS://WWW.FACEBOOK.COM/261377963890954_1576566649038739	Radio24syv	05/02/2017 09.30	-0,397
HTTPS://WWW.FACEBOOK.COM/12860228293_10155744584973294	Politiken	02/02/2017 20.21	-0,393
HTTPS://WWW.FACEBOOK.COM/12787473132_10154283282873133	Berlingske	29/01/2017 12.45	-0,388
HTTPS://WWW.FACEBOOK.COM/63503662682_10154395672142683	Jyllands-Posten	30/01/2017 11.32	-0,384
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1843514845933369	Politiko	04/02/2017 16.31	-0,382
HTTPS://WWW.FACEBOOK.COM/1470588026559388_1841748046110049	Politiko	01/02/2017 08.30	-0,376
HTTPS://WWW.FACEBOOK.COM/106526434713_10155160414524714	TV 2 NEWS	31/01/2017 18.50	-0,375
HTTPS://WWW.FACEBOOK.COM/143859902321643_1575279132513039	Debatten - DR	28/01/2017 08.00	-0,372
HTTPS://WWW.FACEBOOK.COM/143859902321643_1584032108304408	Debatten - DR	04/02/2017 09.00	-0,37

Looking back at Figure 8.13-A, the week around January 24th 2016 is a time with particularly low levels of cross-cutting agreement, especially given that levels of initial disagreement are only slightly above average during the same period. It demonstrates how a small selection of special news stories are able to set off discussions where users are unlikely to reach agreement across political lines. Taking a quick look at the posts that produced the most disagreement around this time, almost all of them are related to a specific vote in parliament, which resulted in an unprecedented tightening of the quota for asylum seekers in Denmark. Part of this piece of legislation also allowed the government to seize the belongings of asylum seekers upon their entry into the system. (Crouch & Kingsley, 2016.). The story also reached the international press since the vote at the time made Denmark one of the countries with the most unfavourable conditions for asylum seekers in Europe. Compared to the case with the migrant caravan around September 6th 2015, the news about this legislation does not appear to be have swept across the whole media landscape to the same degree, but for those who participate the discussion is at least as polarizing as the one concerning the migrant caravan.

Overall the patterns pertaining to initial disagreement with varying levels of cross-cutting agreement across political lines through subsequent interaction and commenting demonstrates that political polarization can appear both as a sweeping effect that seems to frame the whole political discussion on social media, as in the case with the migrant caravan, but also with less uniform effects where initial disagreement does result in higher than expected levels of cross-cutting agreement among the users.

Modelling cross-cutting agreement

The purpose of this subsection is to further explore patterns pertaining to cross-cutting agreement in public Facebook discussions. One can only assume that cross-cutting agreement is caused by a complex set of factors and highly dependent on context. An advantage of cross-cutting agreement is that the value is determined as a relation between what happens at the post *and* comment levels of interaction. This allows for cross-cutting agreement to be considered at both levels, while the comment-level provides a much more fine-grained analysis of cross-cutting agreement.

In order to compare predictors of cross-cutting agreement with previous models a simple regression model is applied at the post level using cross-cutting agreement as the dependent variable. Figure 8.15 shows that cross-cutting agreement is positively correlated with overrepresentation of women and negatively correlated with harsh language. The primary significance of this finding is that use of harsh language is shown to be an exacerbating factor for political polarization in discussions on Facebook. Discussions that have high initial disagreement, based on users' initial reactions to the published content, can attain high levels of cross-cutting agreement in the comment feed if comments are kept civil. Even though initial political disagreement is positively correlated with harsh language use, there are indeed variations based on how much agreement is reached through subsequent interactions. Discussions that have lower levels of harsh language have higher levels of cross-cutting agreement, indicating that civility might indeed be a component in creating consensus, though no causal relation can be proved at this stage.

It can be observed that certain topics such as Refugees and Integration as well as page categories like Political News and Right Leaning News are more likely to produce discussions that do not reach agreement.

FIGURE 8.15 – OLS RESULTS CROSS-CUTTING AGREEMENT ~ *, POSTS, SIMPLE

DEP. VARIABLE:	**CROSS_AGREEMENT**	**R-SQUARED:**	**0.147**	
MODEL:	OLS	Adj. R-squared:	0.147	
METHOD:	Least Squares	F-statistic:	724.8	
DATE:	Thu	31 Oct 2019	Prob (F-statistic):	0.00
TIME:	07:56:18	Log-Likelihood:	94294.	
NO. OBSERVATIONS:	193540	AIC:	-1.885e+05	
DF RESIDUALS:	193493	BIC:	-1.880e+05	
DF MODEL:	46			
COVARIANCE TYPE:	nonrobust			
	coef	std err	t	P>|t|
CONST	0.2873	0.018	16.120	0.000
REFUGEES_AND_INTEGRATION	-0.2043	0.004	-54.587	0.000
WOMEN_COMMENTS	0.0717	0.002	37.229	0.000
AGG_HATE_PROBABILITY	-0.1506	0.004	-41.613	0.000
REACTIONS_TOTAL	-0.0489	0.002	-20.650	0.000
O	-0.0697	0.002	-33.476	0.000
TABLOID	0.0189	0.002	11.687	0.000
POLITICAL_GAMES_AND_REFERENDUMS	-0.1673	0.009	-19.175	0.000
LOCAL NEWS	0.0182	0.002	9.742	0.000
V	-0.0803	0.002	-35.254	0.000
B	-0.1140	0.003	-37.405	0.000
GENERAL NEWS	0.0011	0.001	0.799	0.425
OE	-0.0954	0.003	-36.118	0.000
A	-0.0851	0.002	-36.156	0.000
SAD_TOTAL	0.0189	0.004	4.370	0.000
I	-0.0658	0.003	-25.119	0.000
HEALTH	0.0904	0.007	13.332	0.000
ECONOMY	-0.0386	0.006	-6.108	0.000
F	-0.0895	0.003	-31.102	0.000

RELIGION	-0.0244	0.004	-6.492	0.000
POLITICAL NEWS	-0.0636	0.003	-23.768	0.000
ANGRY_TOTAL	0.0403	0.002	20.614	0.000
AA	-0.0788	0.003	-26.511	0.000
INFOTAINMENT	0.0129	0.002	5.483	0.000
NB	-0.0943	0.007	-13.720	0.000
LEFT LEANING NEWS	-0.0580	0.003	-22.050	0.000
CLIMATE_AND_ENVIRONMENT	-0.0563	0.009	-6.046	0.000
CULTURE	0.1182	0.008	14.665	0.000
COMMENTS_TOTAL	-0.1902	0.018	-10.718	0.000
SPORT	0.0866	0.006	14.009	0.000
LO	0.0335	0.004	8.369	0.000
RIGHT LEANING NEWS	-0.0220	0.002	-11.033	0.000
LOVE_TOTAL	-0.1350	0.010	-13.343	0.000
FREDERIKSBERG KOMMUNE	-0.0663	0.005	-12.147	0.000
JUSTICE_AND_SECURITY_POLICY	0.0857	0.004	19.830	0.000
BRØNDBY KOMMUNE	0.1097	0.010	10.450	0.000
CHARITY	0.0512	0.011	4.732	0.000
RINGKØBINGSKJERN KOMMUNE	0.0762	0.017	4.485	0.000
FTF	-0.0235	0.004	-6.003	0.000
EDUCATION_AND_RESEARCH	0.0854	0.009	9.399	0.000
RANDERS KOMMUNE	0.1118	0.020	5.558	0.000
TECHNOLOGY_AND_DIGITALIZATION	0.1030	0.009	11.098	0.000
C	-0.0148	0.003	-4.783	0.000
DEBATE	-0.0183	0.003	-6.325	0.000
EMPLOYMENT_AND_THE_LABOR_MARKET	0.0821	0.007	11.449	0.000
DOMESTIC_POLICY	0.0347	0.005	6.442	0.000
AABENRAA KOMMUNE	-0.0548	0.086	-0.638	0.523
OMNIBUS:	15360.899	Durbin-Watson:	1.915	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	26954.521	
SKEW:	-0.582	Prob(JB):	0.00	
KURTOSIS:	4.409	Cond. No.	438.	

In order to get a better grasp of the complexity involved in cross-cutting agreement its determining factors are modelled at the comment level. This entails considering the characteristics of individual comments that contribute to the average cross-cutting agreement of a given post. Another regression model using cross-cutting agreement as the dependent variable is created but using input data calculated at the comment level. This is done with the same formula as in Equation 8.0 where it is based on the subsequent agreement score for a single comment instead of it being the mean of all subsequent agreement scores of comments made to a post. The model considers the interaction between parameters such as the topics, the page categories, harsh language and whether the comment is made by a female participant or not as well as the rest of the base variables. Since the model is now considering single users who are writing comments it should also include the multiparty perspective with respect to the predicted voting intention of the users and not just the political left- and right-wing scale. This way it is possible to explore the relations between user interaction in spaces, across topics, moods and demographics at a very fine-grained level. It also means there is a very large number of potential parameters to evaluate in the model selection process, and since there are lots more comments than posts, computational resource limitations dictate that the model be limited to a sample of 500.000 randomly selected comments. After non-null filters and model selection the final model contains a total of 433.132 observations and 388 parameters (a single parameter can potentially represent the interaction between up to four parameters). The results of the final model, which is illustrated in Appendix 8.3-SI will now be covered starting with the linear parameters and then on to more complex ones[32].

There is a total of 49 linear, non-interaction parameters, and most of them are in the top 100 of most influential parameters. Unsurprisingly, harsh language and topics related to refugees and immigrants are negatively correlated with cross-cutting agreement, which is in line with the overall pattern seen in the analysis so far. It can also be seen that the length of a comment, meaning how many words it contains, is one of the strongest positive correlations with cross-cutting agreement. It is likely that longer comments contain more details or more well-thought out arguments, which might be more appealing to a broader political spectrum. The single strongest parameter, which is a negative coefficient, relates to whether the comment is made by someone who votes for the Danish Folkparty (DF), which is the mainstream populist party. Harsh language appears to be a moderator between comments made by DF voters and likelihood of *not* creating cross-cutting agreement. This means that harsh language moderates the strength of the first parameter such that a person voting for the Danish Folkparty is even less likely to cause cross-cutting agreement if they use harsh language.

[32] The Figure is too large to include in the main text.

We see a number of other moderation effects related to comments made by DF voters such as if the comment is made by a woman or in response to topics such as employment and labour market, social policy, education and domestic policy where the moderation creates a positive correlation with cross-cutting agreement. It means that a DF voter, who is a woman or someone who makes a comment to posts about the topics just mentioned mitigates a lot of the negative correlation between being a DF voter and not causing cross-cutting agreement. On the other hand, topics such as immigration, religion and foreign policy increase the strength of the negative correlation between comments made by DF voters and cross-cutting agreement.

It is also interesting to note how the parameters: 1) topics related to immigration, 2) comments made by DF voters and 3) harsh language are, independently, negatively correlated with cross-cutting agreement, meaning that any discussion containing those elements are less likely to produce the kinds of interaction that will create agreement across political lines. However, there are exceptions such as when harsh language is moderated by posts related to domestic policies or when DF voters comment on economy related stories using harsh language, which are both cases that involve harsh language, but results in a positive relationship with cross-cutting agreement. Most impressively, three of the parameters which are individually some of the strongest negative predictors of cross-cutting agreement (comments made by DF voters, immigration related topics and harsh language) when combined into a single parameter are alleviated of their negative correlation when moderated by Tabloid news sources. These disjoint non-linear effects provide insights into the complex distribution of discussions that can potentially produce agreement and disagreement across the different public spaces. It is a testament to the importance of context when it comes to content consumption and social interactions. There is likely a specific subset of people who are able to find each other and reach agreement when discussing refugees and immigration in the aftermath of tabloid stories.

Media outlets in the category of political news are less likely to cause users to reach agreement compared to other spaces, but all topics that are not related to immigration, religion and foreign policy seem to moderate this relationship and invert the effect, suggesting that many political discussions can actually produce above average levels of cross-cutting agreement as long as they are not related to a few controversial topics. This is further supported by results shown in the previous figure 8.14, which indicate that the two topics Refugees and Integration and Religion are the only ones that appear to reach lower levels of cross-cutting agreement over time.

Another noteworthy aspect is when users who are predicted to vote for one specific party seek out posts made by politicians from other parties and engage in discussions on their public pages. The model reveals how interaction patterns are not equally distributed across political pages but depends on specific contexts (Appendix 8.3-SI). Unsurprisingly the negative correlations are the strongest ones. Political pages from all parties are negatively correlated with cross-cutting agreement. To clarify what this means, when any user is commenting on posts published by politicians or political parties, those comments are less likely to cause cross-cutting agreement compared to all other pages in the Danish public. The negative correlation is unsurprising because political pages are, within the model, implicitly compared to media and other pages which will often be more neutral and less politically homogenous. It illustrates what one would expect, namely that when users are actively seeking out the political opposition it is more likely with the intention to attack opponents' views, than seek to understand them.

The second tier of strong negative correlations consists of situations where voters seek out posts from their rival parties e.g. Danish Folkparty (DF) voters on Radikale Venstre's (B) pages or Enhedslisten (OE) voters on Venstre's (V) pages, as well as the opposite for positive correlations e.g. Liberal Alliance (I) voters on Venstre's (V), which is natural since they are ideologically closer to each other. Thus, the overall pattern is for users to attack their rivals and agree with their closest political allies.

There are however also some less expected results such as cases where voters of the populist party Danish Folkparty (DF) comment on posts from Enhedslisten (OE) and the Social Democrats (A), which is positively correlated with cross-cutting agreement. Though, further down on the table in Appendix 8.3-SI, this relationship is moderated by use of harsh language such that comments with civil language are much more likely to cause higher levels of cross-cutting agreement compared to the uncivil ones. Furthermore, there is a great variance in terms of which discussions cause users to reach agreement based on which party is posting and the topic that they are posting about. The party Venstre (V) seems split on different topics. Posts related to Climate and Environmental issues only have positive correlations when dominated by commenting users from their own side of the political spectrum (right-wing parties), yet a topic such as Justice and Security shows the exact opposite effect and produces a lot of agreement when published by any of the left wing parties.

Unexpectedly, there is almost no statistically significant parameters related to whether a comment was written by a woman or a man. It runs counter to the previous findings (see Figure 8.15) that an overrepresentation of female participants was more likely to lead to cross-cutting agreement. The best way to interpret the discrepancy between the two results is that a slight overrepresentation of female participants is more likely to cause users to reach agreement across political lines, but it is neither the male nor female comments that make the real difference on average. This is because some comments are somewhat neutral in terms of promoting cross-cutting agreement, thus the cause must be either an overrepresentation of *neutral* female commenters or the female participants are not writing their own comments, but simply liking or otherwise reaction to other users' comments.

Flows of agreement and disagreement

This subsection will dive further into the various directions that public discussions can take. Specifically, this part of the analysis considers the fact that Facebook allows for two steps of commenting on posts. This means that each comment to a post can potentially receive a number of replies and those replies can also receive likes from users. Thus, for each post where the ensuing comments pull the discussion in a direction, towards cross-cutting agreement or not, replies made to those comments can pull the discussion further towards either agreement or disagreement. Thus, comments and replies respectively constitute the first and second step of cross-cutting agreement/disagreement. The calculation for the second step is identical to that of the first, which was covered in the previous subsection, except that it moves one step down in the communications hierarchy such that a reply is to a comment what a comment is to a post. The result of all replies made to all comments on a given post is averaged at the post level.

With this it becomes possible to divide discussions into four categories on a per post level based on whether they 1) move toward cross-cutting agreement, but then revert back to disagreement through replies, 2) move toward disagreement, but achieve cross-cutting agreement through replies, 3) reach no agreement in either comments or replies or 4) move toward cross-cutting agreement and then reach further agreement through replies. Any of these four configurations is termed a *flow group.* These flow groups will, respectively, be denoted as Agree Revert (1), Agree Rebirth (2), No Agree (3) and Full Agree (4). It is, however, necessary to include a fifth category. As mentioned in the previous section, the calculation behind cross-cutting agreement is built on the premise that it is really the results at the extreme ends of the scale that denote either agreement or disagreement, whereas results around the global average are most likely either random patterns (not politically charged) or consist of politically homogenous crowds. For this reason, the four categories just mentioned must be based on whether they are significantly above average in both step one (comments) and step two (replies). Anything that is too close to the average in either step will fall into a fifth category, Mixed Agree (5). The process is illustrated in below (descriptions of variables are found in Appendix 8.0-SI):

FLOW GROUP	CONDITION
FULL AGREE	> 2 * mean(initial_disagree*subsequent_agree) AND 2 * > mean(initial_disagree_comagg*subsequent_agree_comagg)
AGREE REVERT	> 2 * mean(initial_disagree*subsequent_agree) AND < 0.5 * mean(initial_disagree_comagg*subsequent_agree_comagg)
AGREE REBIRTH	< 0.5 * mean(initial_disagree*subsequent_agree) AND > 2 * mean(initial_disagree_comagg*subsequent_agree_comagg)
NO AGREE	< 0.5 * mean(initial_disagree*subsequent_agree) AND < 0.5 * mean(initial_disagree_comagg*subsequent_agree_comagg)
MIXED AGREE	Matches none of the conditions above

It should be mentioned that far from all posts have enough activity and political penetration in both steps to reliably calculate the flow group. Only posts that have at least 10 comments and 10 replies with at least 85% political penetration are included in the final sample, which comes to a total of 86.713 posts with close to 4/5 being from media pages. The distribution of initial disagreement and cross-cutting agreement do not vary much between the full sample from the previous subsection and the reduced one used for the calculation of flow groups. It will be assumed that the slicing of the sample is close to random with respect to the variables of interest here. As an example, if one compares the means of the variables found in Table 8.10 (the subsample) with the same means of the entire sample, no significant difference is observed ($p > 0.05$)

Agreement flows in relation to popularity, gender, emojis and incivility

After dividing all posts into distinct groups based on the flows of agreement/disagreement we can check them against a few simple statistics. Table 8.10 illustrates that there is very little variation between the groups when it comes to average reactions and comments received per post. The Mixed Agree group has a much lower average for number of comments received, but this is to be expected as posts with relatively few comments are unlikely to have agreement flows that veer far from the global averages.

TABLE 8.10 – MEAN NUMBER OF INTERACTIONS PER FLOW GROUP

FLOW_GROUP	LOVE_TOTAL	LIKE_TOTAL	ANGRY_TOTAL	SAD_TOTAL	COMMENTS_TOTAL	REACTIONS_TOTAL	SHARES
AGREE_REBIRTH	0,021187	0,805058	0,096082	0,032079	0,021187	0,782828	112,1604
AGREE_REVERT	0,019288	0,77832	0,112265	0,038234	0,019288	0,781764	95,05953
FULL_AGREE	0,019622	0,783071	0,110291	0,035617	0,019622	0,763479	126,6168
MIXED_AGREE	0,012407	0,791224	0,12009	0,042846	0,012407	0,770923	155,9113
NO_AGREE	0,0175	0,833879	0,087645	0,026011	0,0175	0,784597	133,749

There is a bit more variation when it comes to average number of shares received per post. The flow group Mixed Agree has, by far, the highest average of shares. To reiterate, Mixed Agree will typically contain two types of posts: 1) posts that have very little to do with politics and 2) posts with participants that are too homogenous to cause any great variation in political agreement and disagreement. Since it was shown in an earlier subsection that homogenous posts are not correlated with shares (see Figure 8.8), this most likely means that posts which are less likely to have political content or overtly promote a political position are shared the most. The group with the second most shares on average is No Agree, which indicates that divisive and polarizing discussions are likely to spread farther than de-polarized ones. The mean share value between the No Agree group and the rest differs enough to be statistically significant ($P < 0.0001$), but the difference is still much smaller than the difference between Mixed Agree and all other groups. Thus, No Agree discussions are, comparatively, not that much more likely to be spread further.

In line with previous results it can be seen that, when accounting for the full flow of agreement and disagreement, harsh language and high numbers of male participants are both more prevalent for the No Agree group, whereas the opposite can be said about the Full Agree group. There are no clear differences between the Agree Rebirth and Agree Revert groups.

Emoji responses do not appear to differ too much between the different groups, which is somewhat expected since they have not appeared to play big roles in the previous regression models. The biggest relative difference is the average number of sad emoji responses, which is smaller for the No Agree group. It makes some sense that stories, which initially make people sad, could more easily unite people across the political spectrum. The No Agree group also has the lowest average of angry emoji responses, which can seem a bit unexpected. However it was shown in Figure 8.8 that angry responses were strongly correlated with politically homogenous environments so it makes sense that the Mixed Agree group has the highest average of angry responses.

Distribution of agreement flows across topics and spaces

This part explores how flows of agreement and disagreement are distributed across different spaces and topics. Political pages and media pages have a much higher percent of activity per post than the other types of pages in the Danish collection, and thus these are the only ones that will be included here, since the rest simply do not have enough posts that qualify for calculating the full flow of agreement and disagreement to reasonably compare all different spaces that exist within them.

Figure 8.18 shows a heatmap illustration of how many posts can be found within each category for each flow group among all media pages. Each category is normalized by its sum such that large categories like General News are put on the same scale as smaller ones like Debate. Furthermore, each flow group is standardized across all categories, such that the value for a given cell is a number between 0 and 100, which represents how close a given category is to having the highest number of posts within one of the five flow groups.

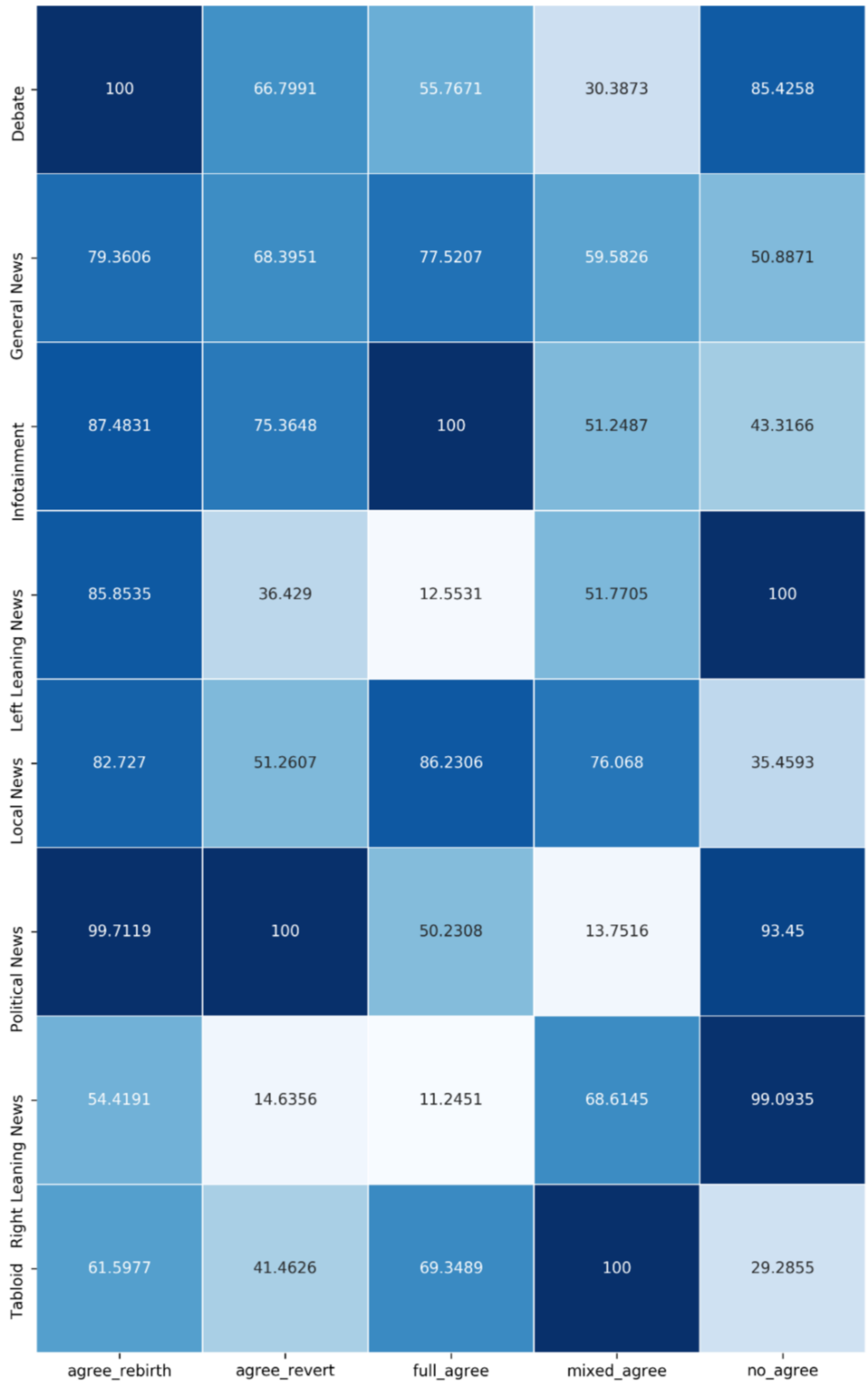

FIGURE 8.18 – INDEX SCORES FOR EACH FLOW GROUP PER MEDIA CATEGORY

P < 0.0001 USING FISHERS EXACT

Agree Rebirth and Agree Revert are most prevalent for Political News and Debate. This gives the impression that pages within these categories are functioning as spaces of free debate, where the direction towards either cross-cutting agreement or disagreement can take multiple forms and easily change direction. Left Leaning News and Right Leaning News represent the spaces that produce most posts in the No Agree group. This suggests that those who seek out these spaces might have less motivation to discuss and learn and are more interested in challenging the political opposition. They both have by far the lowest number of posts in the Full Agree category. Though we do also see a fair amount of posts in the No Agree group for both Debate and especially Political News, which suggest that spaces that are framed as political are less likely to inspire cross-cutting agreement.

The posts from the Full Agree group are most often found on infotainment pages. This can seem both trivial and curious at the same time. At first it might not be surprising that spaces with less political talk produce more cross-cutting agreement however, the calculation behind the flow groups is configured so that cross-cutting agreement only reaches high levels when the initial story presented in the post is at least potentially polarizing. A post cannot be in the Full Agree group unless there is some evidence that the users who engage with it have positioned themselves with respect to their voting intention. Thus, it is warranted to consider the de-polarizing effect that political discussion in non-political spaces might have.

The page categories with the second and third highest number of posts in the Full Agree group are Local News and General News. The pattern here seems to be that users are not actively looking for political content or expecting other users to be guided by their political beliefs in the way that they engage with content. Instead they are commenting on issues of common concern based on more basic everyday life motivations and do not necessarily view the space as a political battleground.

Figure 8.19 shows the distribution of flow groups across page categories that correspond to which political party the page belongs to. Here we see that the Conservative party (C) has by far the highest amount of posts in the Full Agree and Agree Rebirth category. To a political scientist this may seem a bit surprising since they are usually not considered a centre-right party like for example, Venstre (V). However, it makes sense considering that the Conservative party is both one of the smaller parties, but also, and most importantly, has one of the least concrete stances on controversial issues such as refugees and immigration. As we have seen earlier, content related to immigration, refugees, religionand foreign policy are strongly negatively correlated with users' abilities to reach cross-cutting agreement. We see that another one of the smaller right-wing parties, Liberal Alliance (I), dominates the Agree Revert group. It means that discussions on their pages are more likely to end on a disagreeing note even if it initially was en-route to cross-cutting agreement. An in-depth analysis would be needed at this point in order to make an educated guess of why this is the case.

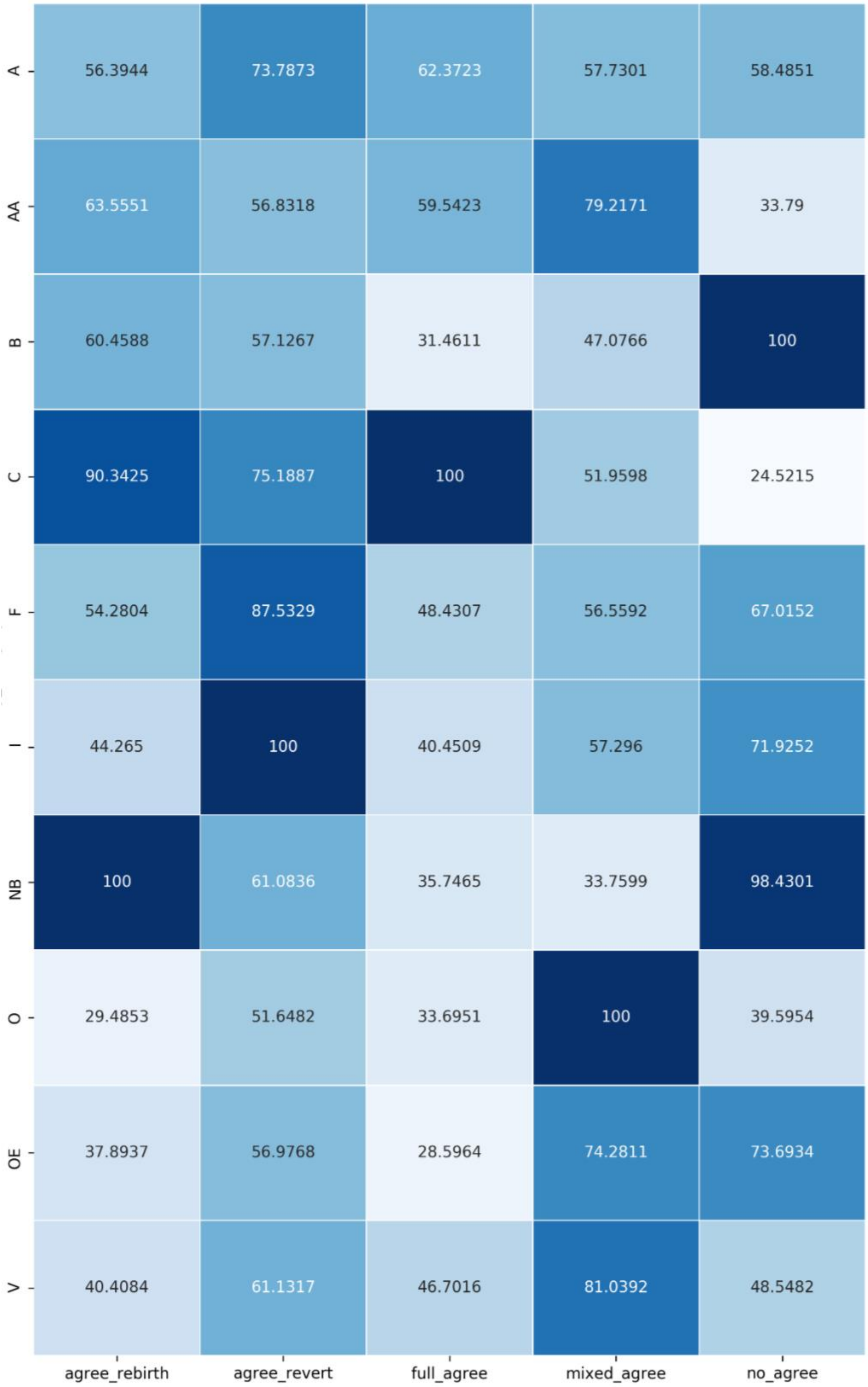

FIGURE 8.18 – INDEX SCORES FOR EACH FLOW GROUP PER POLITICAL PARTY.

P < 0.0001 USING FISHERS EXACT

It was mentioned in the previous subsection how comments made by Danish Folkparty (O) voters was one of the strongest predictors of discussions with cross-cutting disagreement. It might initially seem strange that they have a small number of posts in the No Agree group, but this makes sense since these are political pages and Danish Folkparty has the highest levels of political homogeneity. Thus, they dominate the Mixed Agree group and have low scores in all other groups. Posts within the No Agree group are most often found on pages that represent Radikale Venstre (B), which is famous for being a very centrist party with a little bit of a 'homelessness syndrome'. They are more similar to right-wing parties on economic and tax related issues, but more similar to the left on issues related to immigration, education and political correctness.

Finally, Figure 8.21 shows the distribution of posts across topics and flow groups. What stands out the most is how much the No Agree group is dominated by just two topics Refugees and Integration and Political Games and Referendums. As explained earlier the latter topic is not very interesting since it mostly contains stories related to poll results. That immigration related issues dominates this group so heavily does bear witness to the notion that political polarization happens mostly along a single topical dimension. This is supported by the fact that posts from the Full Agree group are much more evenly distributed across many topics, especially those related to health, education, culture, employment and everyday life. Foreign policy issues, which are often related to immigration in some way, elicit very different patterns compared to those that are directly about immigration and refugees. The Foreign Policy topic is prevalent in both the Agree Rebirth and Agree Revert categories and is also relatively high scoring in the Full Agree group demonstrating the true difference between the two topics (immigration and foreign policy). Looking more qualitatively into posts for these two topics might help shed some light on exactly what makes some stories more polarizing than others. A similar observation can be made for the topic Religion.

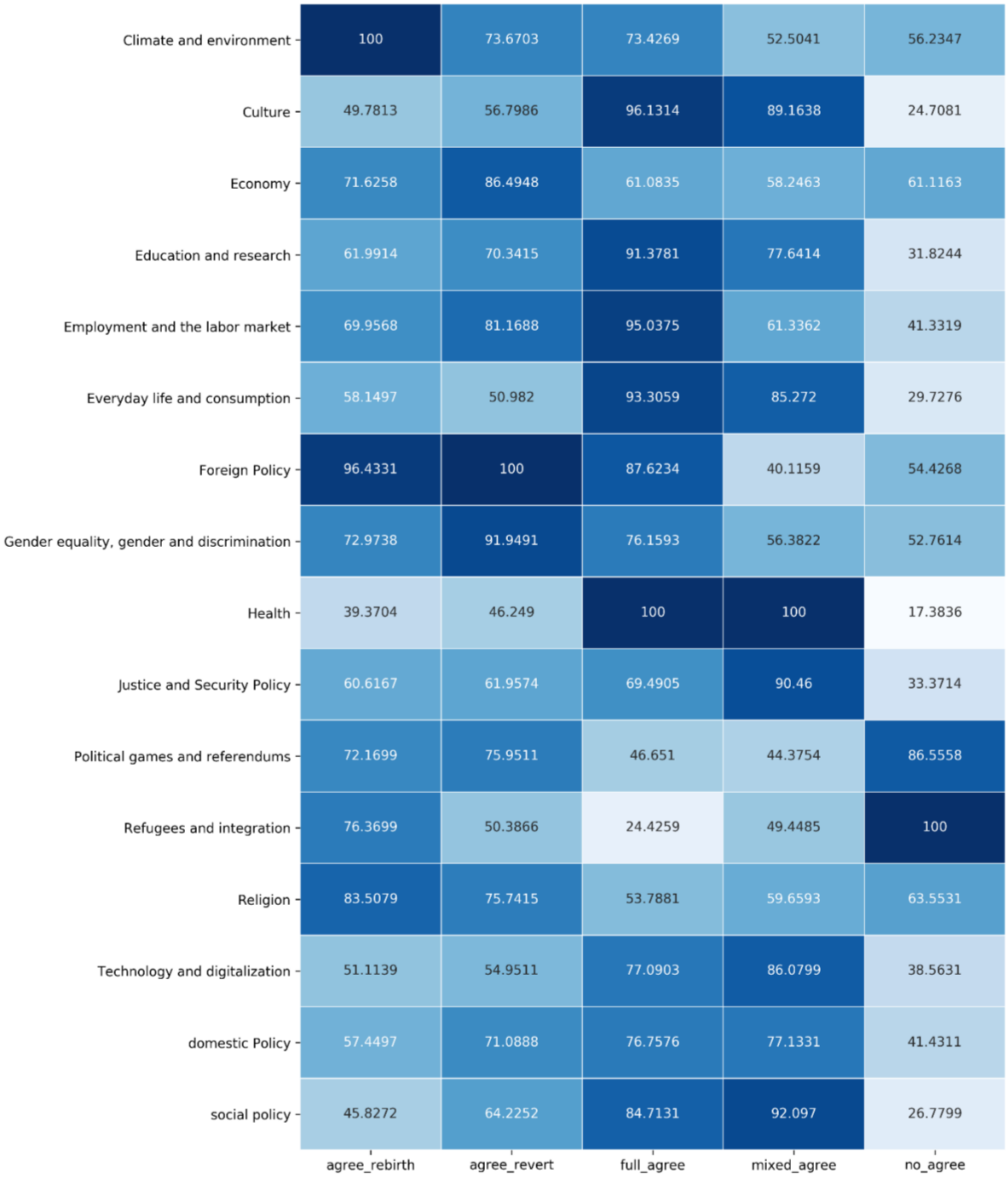

Figure 8.21 – Index scores for each flow group per topic.

P < 0.0001 using Fishers Exact

Progression of individual discussions

The purpose of this section is to analyse the progression of a single discussion as it develops from the initial publishing of a post to the last comment/reply. This entails looking at how levels of political homogeneity, cross-cutting agreement and harsh language use change over the course of a single discussion. However, it is not a case study of a selected discussion, but an average of all discussions. This will provide an insight into whether political polarization is in general likely to increase over the course of any given public Facebook discussion in the Danish public space.

Similar to the flows of agreement and disagreement analysed in the previous section, the change in values over the course of a single discussion is not relevant for posts that only contain a few comments. Thus, we will choose a filter similar to the one used in the previous section. Only posts that have at least 20 comments or replies with at least 85% political penetration will be used, which comes to a total of 89,114 posts and 3,596,047 comments/replies to be analysed.

Progression in this context can essentially be understood as the lifecycle of a discussion. However, because the so-called lifecycles of individual discussions do not have equal time spans, some will finish after just a few hours while others last several days. It must of course be assumed that the length of the time span impacts the progression of the discussion, but since the focus is on very broad trends it can also be assumed that if there are significant differences between long and short time span discussions, it would gain some expression in the observed trends. The underlying assumption is that, independently of how long the time span of a discussion is, from the moment the first comment is made the people who are exposed and choose to engage will be somewhat determined by personal, social and algorithmic curation logics. The purpose of this analysis is to consider whether these curation logics push discussions toward increased political homogeneity, cross-cutting agreement and harsh language use.

In order to compare the progression of discussions with varying numbers of comments and varying time spans it is necessary to consider each comment/reply as a single step forward in time independently of how much time passes between two steps. It is also necessary to apply a smoothing effect so that all discussions have the same dimensions. The average number of comments/replies on posts, after applying the aforementioned filters, is 55. Discussions with more comments will be compressed and discussions with fewer will be stretched so that all discussions take place over the course of 55 steps in time. The function for compressing the timelines of discussions is documented in Appendix 8.4-SI.

The main result is displayed in Figure 8.22. We see that political homogeneity and use of harsh language show a clear tendency to increase on average as a discussion continues. Cross-cutting agreement shows a weaker, but still politically significant (P < 0.00016) tendency to decrease over the course of a single discussion. All in all, the general trends point towards an average increase in polarization, both as increased homogeneity as well as increased disagreement.

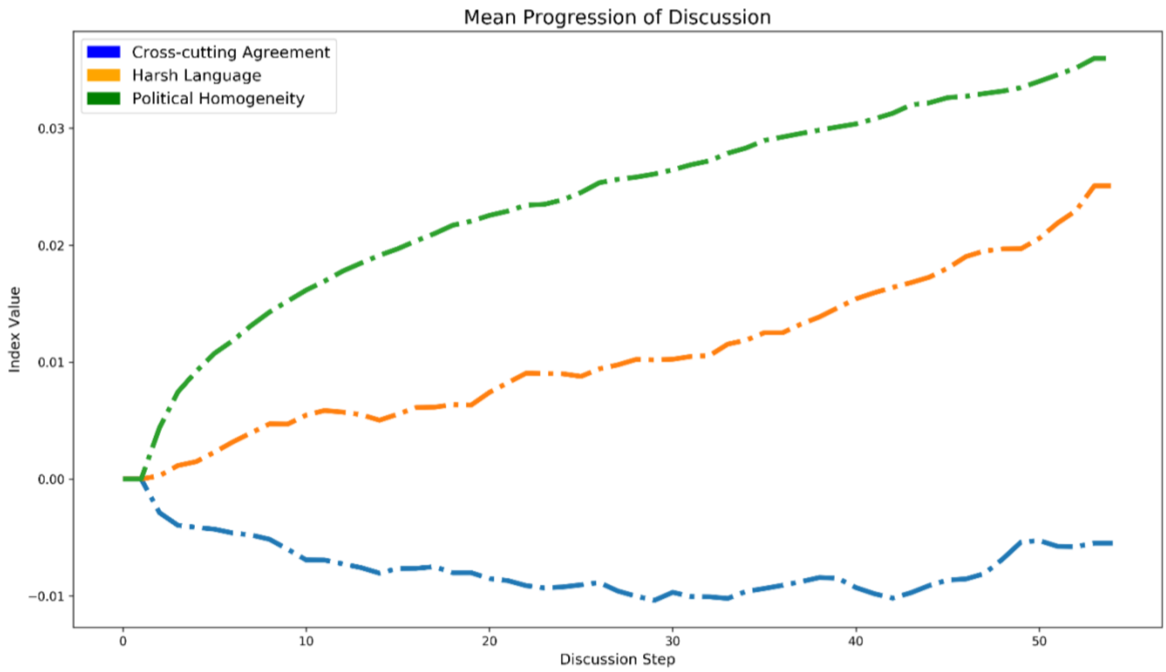

FIGURE 8.22 – INDEX SCORES FOR EACH FLOW GROUP PER TOPIC

While the overall trends shown in figure 8.22 are fairly clear there are exceptions based on topics of discussion and the spaces in which they occur. Additional examples can be found in Appendix 8.2-SI. A topic like Economy stands out by having cross-cutting agreement that is increasing rather than decreasing as well as a much lower end value for political homogeneity when compared to the general trend. A related topic like Employment and Labour Market displays homeostasis of cross-cutting agreement. Topics such as Social Policy and Domestic Policy do not have increasing values of harsh language use.

For different categories of pages there is a very obvious exception for spaces that are politically charged. All political pages along with right leaning news and left leaning news display a decrease in political homogeneity the longer a discussion continues. Pages within these categories can be assumed to have a high degree of average political homogeneity, which means that a small decrease in homogeneity is not equal to a highly diverse crowd at the end of the discussion. However, it is interesting because it seems to suggest that more 'outside fuel' is needed as discussions progress in these spaces. It is possible to conceive a kind of inflation point for political homogeneity on Facebook. The idea would be that discussions which originate from spaces that have a certain level of political diversity have a tendency to move towards greater homogeneity, but spaces that reach very high levels of homogeneity will begin to have opposite tendencies. Though it is unlikely that such an inflation greatly determines patterns of polarization. Political News and General News and Tabloids for example all have high political diversity, but still elicit different patterns. While Tabloid media and General News follow the general trend on all three counts, the Political News and Debate categories displays homeostasis with respect to cross-cutting agreement.

This chapter has demonstrated how digital trace data from public pages on Facebook can be effectively leveraged in order to extract patterns pertaining to political homophily and cross-cutting agreement. Furthermore, the results from this chapter provides additional empirical evidence for some of the forces that govern social media behaviour with respect to political communication. The specific findings only pertain to Danish public pages on Facebook, however the findings are still relevant for the discussion about the general expectations on social media.

There is evidence to suggest that political homophily does increase over time, though significant increases are heavily dependent on the types of pages, activities and topics discussed, thus hypothesis H1-A is partially confirmed. Cross-cutting agreement shows an overall increase over time, though still somewhat dependent on types of pages and topics discussed, which means hypothesis H1-B is partially rejected. For single discussions political homophily appears to be increasing the longer they remains active on average, which confirms hypothesis H2-A. However, hypothesis H2-B is rejected since cross-cutting agreement does not show a clear trend of either increasing or decreasing.

High levels of political homophily is heavily skewed towards certain types of pages and topics. Media pages that are particularly popular with voters of populists parties such as Dansk Folkeparti (O) and discussions about refugees and immigration have significantly higher levels of political homophily compared to many other pages and topics. The same can be observed for low levels of cross-cutting agreement. As such hypotheses H3-A and H3-B are confirmed. Political homophily is strongly correlated with anger and incivility, and cross-cutting agreement is negatively correlated with incivility though not the same degree of statistical significance. As such hypothesis H4-A is confirmed and H4-B is partially confirmed.

The next chapter will offer a more in-depth discussion of the results, both those that relate to the hypotheses and those that go beyond.

Chapter 9. Discussion

The analysis in the previous chapter provided insights into macro trends pertaining to political homophily and polarization over time, across pages, topics and other factors such as incivility and sex. Furthermore, the chapter demonstrated the application of the specific set of methods developed in this project and how they can be leveraged when combined. This chapter will discuss the implications of both the concrete results and the methods as tools for enriching public opinion formation processes.

The discussion is split into two main parts. The first part will discuss the results presented in chapter 8 relating it to previous research into political polarization and disagreement on social media. The second part will extend the discussion from the first part by addressing how the results and methods used to obtain them relate to the concept of the public as an opinion forming body.

The Evolution of Political Polarization in the Danish Public on Facebook

The results presented in the analysis provide a counter-narrative to the idea that social media is increasingly causing users to engage with content that is aligned with their political preferences. We do see some public pages that are heavily dominated by users who are politically similar, which is not completely unexpected, especially given that many pages are relatively small. The more activity there is on a single page, the less likely it is for users on that page to be politically homogenous. Overall there is no significant increase in political homogeneity over time, except for political pages where we do witness an approximately 8% increase between 2014 and 2018. Furthermore, pages that are increasing in homogeneity are more likely to be decreasing in weekly activity over time. Thus, an increase in political homogeneity can, on average, be considered a negative influence on the popularity of a Danish Facebook page, which can be interpreted as a disincentive to seek homogeneity over heterogeneity.

If filter bubbles are an ever-present and ever-growing phenomenon, even if only slightly, we would expect political homogeneity to gradually increase over time. As Bechmann &

Nielbo (2018) mentions, perfect homogeneity is rarely the case and it is difficult to determine the threshold that decides whether a space constitutes an echo-chamber or not. Such observation resonates well with this project since no single page in this analysis has a homogeneity score of 1[33]; only a few obscure political pages even come close. However, it is possible to use the results to point out potential 'relative' echo-chambers. It was shown how the right-wing populist media pages Newspeek Network and Den Korte Avis can be considered true outliers in that they have very high homogeneity scores compared to how much weekly activity they also generate. Coincidentally both of them along with a few other populist pages are among a rare subset of pages that have seen both a surge in popularity as well as a significant increase in political homogeneity. The point to be made here is that the possibility for some spaces to emerge as self-reinforcing echo-chambers seems very real, even if it is not the norm among public pages on Facebook. Curiously the set of pages that qualify as being echo-chambers for the far-left include mostly charity organizations. With this note it seems appropriate to mention that these are just Facebook pages and cannot be used as evidence that people who vote for left-wing parties give more to charity; it rather suggests that being involved with charity organizations is more important for the leftist identity in Denmark.

As was noted in the previous chapter, pages that have generally increased most in popularity, aside from the populist pages just mentioned, are those with higher than average political homogeneity in total, but with a gradual decrease in homogeneity over time. This offers some support to the idea that a higher level of homogeneity is good for mobilization (Obar, Zube & Lampe, 2012), but it also suggests that gradually attracting more diverse user bases provides more long-term popularity than the echo-chamber model, with the exception of pages associated with the political far-right. Additionally, the fact that there is an increase of homogeneity on political pages, but a significant decrease on those media pages which specialize in political news suggests that political pages are increasingly being used as mobilization grounds, or 'political safe spaces' (Hibbing & Theiss-Morse, 2002), while some politics focused media pages, perhaps representing a more neutral space, become battlegrounds where users go to exercise their political identity and engage in debate with users from the entire political spectrum. The argument that media pages are increasingly taking the role as places of political

[33] In chapter 6 it was explained how the level of homogeneity is measured using a scale between 0 and 1. Thus a 1 represents a perfectly homogenous crowd.

debate is underlined by the fact that media pages overtake political pages with respect to levels of initial political disagreement by the end of 2017.

The increased confidence that users might have in their political identity resonates well with the fact that politics focused news pages are seeing the sharpest increase in initial political disagreement. From how initial disagreement is calculated, it is likely to increase because of personal and social curation which covers the scenario that users engage with news stories based on their political preferences rather than other aspects of their identity. However, part of it could also be journalistic curation since it is possible that stories are increasingly being presented with headlines that are designed to incite political disagreement (Martin & Yurukoglu, 2017). Many of the pages within the category of political news are those that have seen a significant increase in popularity and decrease in political homogeneity. Such evidence provides a counter-narrative to the idea that increased exposure to a diversity of opinions produces detachment from politics (Mutz, 2006). Although it is possible that users who seek out political news hubs belong to a special group of people who are generally resistant to detachment.

Media pages that appeal to broader audiences than politics focused media outlets also elicit different patterns. Tabloid and general news media are increasing in both political homogeneity and initial disagreement, especially for topics related to immigration, refugees and religion. This can be interpreted as a sign of political polarization since it likely means that discussions are increasingly being separated into those that are either politically homogenous or politically divisive. One of the most noticeable patterns that seems to explain this trend is the fact that many posts are either dominated by only right-wing voters, or they are published stories that resonate with a left-wing worldview, but are then challenged by right-wingers in the comment section. As mentioned in chapter 8, one would typically expect political disagreement to go down on average when political homogeneity increases, which is often not the case for media outlets in the Tabloid and General News categories. Considering how distinct and strange this pattern is, it could be a consequence of social and journalistic curation logics being combined with algorithmic curation resulting in left-wing voters only being exposed to stories they agree with while missing those that they would normally seek to challenge. A few exceptions exist for the Tabloid and General News categories; left-wing homogeneity is increasing for topics related to gender equality, social policy and culture. Since the curation logics of social media potentially allows for stories to be shared solely within very specific networks of users, it is possible that the publisher is aiming some stories at increasingly narrower segments, at least for some topics (Scheufele & Nisbet, 2013).

It is important to view initial political disagreement as both a positive and potentially negative trait. As mentioned earlier, on the positive side it is an indication that users are exercising their political identity (Dahlgren, 2009, 79), however it can also be an indication of political polarization. For this reason, the concept of cross-cutting agreement was operationalized to provide information about the degree of polarization that could be attributed to a post such that it depended on how much of said cross-cutting agreement could be found in the interaction between users in the comment section. Simply put, interactions between users in the comment section, after a post is published, can act as a qualifier. Even if headlines are polarizing and division is incited, users can either write comments that lead to more polarization or instead create agreement across political lines.

The employment of the measure cross-cutting agreement demonstrates that far from all posts with initial disagreement are polarizing. Some events such as the case of the migrant caravan around September 6th 2015 could be considered manifestations of political polarization since initial political disagreement for this point in time was extremely high with cross-cutting agreement being fairly low. On the contrary the local elections in 2017 saw the opposite effect, showing relatively high levels of cross-cutting agreement.

Overall however, cross-cutting agreement shows little change over time, though there is a slight increase for media pages. Taking media pages as an example, if political polarization was truly increasing one would expect cross-cutting agreement to be decreasing to the same degree, and if de-polarization was happening cross-cutting agreement should be increasing together with initial political disagreement. This provides support to the argument that homeostasis with a slight tendency towards de-polarization is the dominant trend. However, even this slight tendency towards de-polarization might be offset by the special case of polarization happening on General News and Tabloid media pages, as mentioned earlier, as well as the fact that homogeneity is increasing on some pages.

The Complex Distribution of Polarization Dynamics

The previous section already touched on several examples where increase/decrease in polarization, either as political homogeneity or lack of cross-cutting agreement, were not uniformly distributed across public discussions, although the overall trend was in favour of homeostasis. In fact, media pages have only two topics for which cross-cutting agreement is not increasing slightly, but actually decreasing: 1) Religion and 2) Immigration and Integration, to which the latter is sharply decreasing.

Discussions with high levels of political homogeneity or initial disagreement without cross-cutting agreement are all expressively correlated with harsh language, overrepresentation of male participants and topics related to refugees and immigration. Since all three appear as some of the strongest coefficients for both homogeneity *and not* cross-cutting agreement it is worth considering them important indicators of polarization[34]. Although these effects can be further moderated depending on the context, which was shown in the analysis of standalone comments and their ability to cause cross-cutting agreement. The length of a comment and the level of civility (using non-harsh language) are two of the strongest predictors for whether a comment inspires cross-cutting agreement. Users who vote for the right-wing populist party, Dansk Folkeparti, are much more likely than any other users to cause further disagreement, though this effect is moderated by sex such that women participants alleviate this effect. Sex in itself however is not a predictor at all, meaning that the comments which cause a discussion to regress toward either agreement or disagreement are not affected by the sex of the commenter, even if an overrepresentation of women in discussions make them more likely to reach agreement. The most plausible explanation for this somewhat strange pattern is that it is the women who *like* the comments rather than the women who write the comments that cause an overrepresentation of women to be correlated with higher levels of cross-cutting agreement. Thus, the overall civility, not using harsh language, is very likely to stimulate consensus in discussions on Facebook, especially when comments are long. Adding more female participants only has an implicit effect towards cross-cutting agreement, meaning a high number of female participants is positively correlated

[34] Though if something is a predictor of polarization it is also a predictor of de-polarization, since the effect can just be inverted.

with increased cross-cutting agreement, even if this is not related to how many of the comments are written by women.

Content about refugees and immigration is much more likely to cause users to not reach agreement, especially with harsh language, however this correlation is again moderated by specific sets of factors. The analysis pointed out how Dansk Folkeparti voters using harsh language in comments about immigrants and refugees specifically on Tabloid media pages significantly increases the chance that some cross-cutting agreement will occur. The suggestion here is that Tabloid media pages provide a space for populist voters to successfully influence some previously uninitiated people with hardline anti-immigrant opinions.

By filtering the data down to only those posts that have a certain length of discussion and level of activity the analysis was able to explore the full flow of cross-cutting agreement and disagreement in both comments and comments to comments, also known as replies. This is because replies provide yet another level of discussion meaning comments and users' interaction with comments can cause some cross-cutting agreement to which subsequent replies can go further in the same direction, causing additional cross-cutting agreement, or in the opposite. The analysis in chapter 8 provided further evidence for how agreement and disagreement in multiple steps are distributed differently across spaces and topics. Some topics such as Foreign Policy, Gender Equality and even Religion are more or less equally distributed across different flows of agreement even if they all have a slight tendency toward not reaching agreement; whereas a topic such as Refugees and Integration shows itself to be very divisive, almost never reaching agreement in any direction. It highlights just how polarizing content related to immigration can be compared to all other topics. Furthermore, the analysis revealed political news and especially partisan news to be the least likely to promote cross-cutting agreement while Tabloid, General News and most significantly Local News showed much higher potential for cross-cutting agreement. It was mentioned in the previous section that General News and Tabloid elicit patterns of polarization based on users' initial engagement with the content, however it can evidently be suggested that some of this is mitigated by how users interact with each other in the comment section. Such observation fits well with previous research that has suggested that online spaces, which do not have political discussion as their primary purpose can set the stage for more progressive exchange of opinions

(Graham, Jackson & Wright, 2016). On the other hand, as was mentioned in the previous section, the Facebook pages in the categories General News and Tabloids have seen the biggest increase in political homogeneity, which could be an indication that users who are not necessarily looking for political news might also be more likely to have a confirmation bias and avoid news that are not aligned with their beliefs (Walton, 2017).

The question of whether social and algorithmic curation on Facebook have an influence on the progression of a discussion was tested by measuring how political homogeneity, cross-cutting agreement and use of harsh language change from the beginning to the end of a discussion. The overall pattern is quite clear: homogeneity and harsh language, on average, increase steadily from the first comment to the last comment/reply of a given post. Cross-cutting agreement decreases but does start to plateau and slightly increase around the last third of the commenting period. This does seem to indicate that the overall pattern is towards polarization since a discussion is more likely to be politically homogeneous, contain harsh language and not reach agreement the longer it goes on. For cross-cutting agreement and especially political homogeneity it is notable that most of the change happens within the first half of the discussion period, which indicates that it is the first part of the discussion that sets the tone and direction. Explanations for this pattern can likely be found in the way users become exposed to content on social media, which is through networks and governed by aforementioned curation logics, specifically because this finding exposes a discrepancy in the distribution of political homogeneity. It is best illustrated by focusing on Political News, which had seen one of the largest decreases in homogeneity over time, as mentioned in the last section. However Political News still follow the same overall pattern as most pages, namely that homogeneity increases the longer a discussion goes on. Different curation logics might affect exposure and engagement in different ways. One suggestion is that some people are motivated to engage with opposing views (personal curation), however there are other forces at work such that if fewer users in a person's network are involved in a discussion they become less likely to be exposed to it if enough time has passed since its inception (social combined with algorithmic curation). It is outside the scope of this thesis to conclude how the different curation logics work together across Facebook in general, but the results at least suggest that they likely manifest in different ways.

Transparency in Information Flows and the Flexible Data Public

Social media publics hold the potential for combining attributes related to voice and aggregation as demonstrated in the triaxial model. The methods developed in this thesis and demonstrated in chapter 8 serve as an example of how this combining of voice and aggregation can be utilized. The great advantage of social media publics in this perspective is that opinions are constructed and shared freely by individuals. There are no pre-determined answer categories like in polls and surveys and people who are part of the public come into contact with one another in a public exchange of opinions, which is one of the important criteria of opinion formation in the deliberation tradition (Splichal, 2012). Voicing opinions are certainly restricted by the architecture of the social media platform (i.e. which emoji responses available to choose from), however such affordances are often regarded as leaving a fair amount of creative expression for the user (Lomborg, 2011). Also, in this specific study most discussions will often have been framed by the original post made by a media organization or politician, but there are few limits to which directions the discussion can take.

The methods demonstrated in this thesis then show how the digital traces produced from the interactions, both between user and content and user and user, can reveal patterns pertaining to political polarization and cross-cutting agreement by parsing and combining these traces in certain ways. In the context of Big Data theory in media and communications research, it takes advantage of the notion of meta-data (digital traces in the form of likes revealing the political preferences of users) as a form of meta-communication (Jensen, 2013). The Big Data approach with its high granularity provides very specific insights into some broad trends across multiple levels such as time periods, spaces and topics, but it also gives the opportunity to zoom in on a single post, comment thread or even a single comment to find an indication about its potential for fostering polarization or cross-cutting agreement.

It is the argument of this thesis that these methods hold prospects for making the information flows on social media more sensible and transparent. The tools currently available on social media platforms, including the algorithms that they are built on, such as the Facebook news feed, which help users navigate information flows on social media, often promote content that is either popular/trending or matches the previously established preferences of users (Nikolov, Lalmas, Flammini & Menczer, 2018). In this perspective it is possible to imagine other tools that could instead promote content based on its level of cross-cutting agreement. Attempts at creating such tools have been made before. This includes one tool employed by the *Wall Street Journal*, which had feeds that showed content by different partisan news sources side-by-side so that a diversity of perspectives was always available (Keegan, 2017). Another tool designed for the Chinese social media platform Sina Weibo allows users to more clearly position themselves as for or against a certain viewpoint by placing their comment in a certain bloc pertaining to a specific issue (Sui & Pingree, 2016). Both these tools are based on a binary prescriptive logic, asking users to choose sides from the beginning so to speak instead of repurposing digital traces as done in this thesis. In this sense, such tools are more focused on framing the actual communication (the principal data), rather than making the meta-communication (meta-data, Jensen, 2013) visible in an aggregated format.

One of the most innovative tools to date with respect to directly taking advantage of the combination between deliberation and aggregation possible with online digital media is the tool Polis employed by the New Zealand online newspaper Scoop NZ. This tool allows users to comment on an issue and then vote on each other's comments with the added functionality that patterns of cross-cutting agreement between groups of yea and nay could be extracted and shown to the engaging public itself. The method used by this tool has a similar logic to those developed in this thesis, however instead of political positions reflecting the party politics of a given country, the Polis tool essentially calculates them on a case by case basis. Another difference, which can be effectively highlighted using the triaxial model, is that the Polis tool presupposes more engagement over ignorance as both the space and issue is politically framed from the beginning. Users are asked to consider and vote on all previous comments before writing some themselves and the debates are also edited by the host (i.e. Scoop NZ staff members). Communication flows on social media, which consist of both highly engaged individuals as well as incidental exposure, can better take advantage of the features of ignorance over engagement that can allow for more and broader strata of participants.

As pointed out several times, there are definite benefits to a public that is placed further out on the engagement axis in the triaxial model, however methods that are directly coupled to the information flow on social media can take advantage of the ignorance of the public, which allows political talk and by extension cross-cutting agreement to arise more organically across spaces and topics that are not necessarily politically framed from the get go.

An example of current research that comes close to exploring avenues similar to those in this thesis is Babaei et al. (2018), who themselves claim to be the first known example of such research. They develop and test a classifier to recognize social media posts with high probabilities of causing cross-cutting agreement that performs fairly well. The biggest differences between their study and this thesis are that 1) theirs is based on the binary Republican vs. Democrat construct, whereas methods in this thesis are designed to handle multiparty configurations, and 2) their study bases cross-cutting agreement on whether or not people from different sides of the aisle agree with the message presented in a news story, whereas this thesis considers cross-cutting agreement as that which unfolds in the interaction between users in the comment section. With respect to the latter, the methods in this thesis takes more advantage of an active voice public, whereas Babaei et al. (2018) relegates the public to the aggregative logic of the audience tradition. Furthermore, their study is based on the assumption that polarization is always bad, and consensus is to be strived for. This assumption automatically leads to ideas that tools should simply promote consensus-oriented content. Given that there are arguments, as have been mentioned, for why social media publics will have a tendency to be oriented towards agonism, having tools to promote consensus might not be a terrible idea, especially since it was also noted that too much polarization is potentially problematic. However, the complexity of pros and cons among different manifestations of the public informed by the triaxial model seems to suggest that tools which promote a more transparent data public altogether might be preferable. The triaxial model is centred on the debates of aggregation versus voice, consensus versus agonism and engagement versus ignorance. There are advantages and downsides to almost any configuration where a collection of people acts as an opinion forming body. Critiquing the conditions for public opinion formation vis-à-vis media technologies can scarcely avoid making normative assumptions about the public on behalf of the public. As mentioned previously, social media publics are likely to be slightly in favour of agonism over consensus and ignorance over engagement. Longer comments are strongly correlated with the likelihood of causing cross-cutting agreement, thus promoting longer comments could be a way to promote engagement over ignorance in the pursuit of mitigating polarization. Additionally, topics such as immigration and refugees are much more unlikely to cause cross-cutting agreement compared to other topics. Promoting those posts and comments that do manage to reach high levels of cross-cutting agreement would be a way to move public opinion further towards the consensus side. However, the real point is to increase transparency of behavioural patterns as they relate to the formation of public opinion. Instead of simply promoting posts that have certain consensus-oriented characteristics, all patterns regarding cross-cutting agreement, polarization and de-polarization in the public should be made public to the public. Taking advantage of the mixing between aggregation and voice that is offered by networked data publics on social media, it becomes possible to envision a public that can better come to understand its own function, at least in concrete manifestations of momentary connectedness produced by posts, tweets, comments, likes and shares.

This turns towards ideas of the knowing public (Kennedy & Moss, 2015), which is related to the briefly mentioned concept of data agency in chapter 2. Publics gain visibility on social media through the aggregation of shares, likes and comments in networked spaces. Social media platforms have tools that allow the public to become aware of itself. The primary tools are typically centred either on implicit user preferences such as in the Facebook news feed (Thorson & Wells, 2017) or general popularity as in the Twitter trends overview (Gillespie, 2012; 2014). Mapping, exploring and knowing publics beyond the tools provided by the social media platforms themselves have generally been restricted to the corporations in charge of the platforms (Williams, 2014) and small groups of researchers with specific technical skill sets and/or privileged data access (Manovich, 2011). Two central aspects when it comes to turning the known publics into publics that are themselves knowing is 1) greater transparency in terms of how algorithms filter and curate information (Couldry & Powell, 2014) and 2) control over the data (including meta-data) that the publics produce (Bates, 2013). A third aspect has to do with empowering the public with the tools that researchers are using to make the public known.

> "*Data analytics (and the representations and visualizations of publics they generate) could provide an invaluable cognitive resource for members of the public to understand each other, reflect on matters of shared concern, and to decide how to act together as publics*" (Kennedy & Moss, 2015, 7-8).

The public itself can gain insights from observing the patterns that arise when single interactions are put into a much larger context, but it can also build bridges to the more formal publics of local communities, governments and politicians (Kennedy, Moshonas & Birchall, 2015). Politicians and some governmental bodies are already spending large sums of money on data and consultants in order to extract the opinions of the public. An active, transparent data public could potentially build a bridge between the formal and informal publics that would benefit both.

Ideas relating to transparent data publics also fit that of the collectively intelligent public, in the form of an ephemeral issue public or counter public, as a resource available to public servants when seeking guidance on specific policy issues (Madsen & Munk, 2019). Methods proposed in this thesis would indeed make it easier for people, be it the general public or policy makers, to quickly discover discussions that are examples of polarization as well as those that cause cross-cutting agreements in relation to a general topic or specific case. It is the argument of this thesis that drilling down into discussions related to politics and finding those arguments or sentiments that appear to create cross-cutting agreement could provide insights for both the informal and formal manifestations of the public. Studying the broader trends as was done as a demonstration of the methods in this thesis could shine additional light on expectations for the future. These potentials should be seen as a direct consequence of the combination of voice and aggregation, which is unique to networked data publics on social media.

Conclusion

This thesis project has been an attempt to look for new avenues for studying and leveraging public opinion on social media. There is a general concern that social media is influencing information flows and opinion formation in ways that are potentially detrimental to democratic institutions and the political efficacy of the public, to which increased political homophily and polarization are often emphasized. In addressing these concerns, this project has sought to develop computational methods with a twofold purpose: to study broad trends of political polarization in the general public on social media; and lay the groundwork for tools that could potentially be employed by the public itself in order to make opinion formation processes more transparent.

Through a review of previous theoretical and empirical literature related to public opinion, social media communication and political behaviour, this project has proposed a framework to expand the general understanding of the function of public opinion in light of specific potentials for political engagement offered by social media technologies, specifically in relation to political homophily and polarization. Based on the conceptions of public opinion in the proposed framework, this project has presented methods that take advantage of the Big Data potential of the accumulation of digital traces from online behaviour in order to examine polarizing/de-polarizing behaviour on micro (i.e. a single discussion) and macro levels (millions of discussions over several years). The methods have been tested using them to study polarization trends in the Danish public on Facebook between 2014 and 2018. The potentials offered by tapping into the data flow from social media and employing a computational framework to output behavioural insights directly have been discussed in relation to the possibilities for the public to reap the benefits of such insights as they engage in activities on social media platforms.

Key Contributions

Despite social media being a nearly two-decade old media concept, the role it plays in the formation of public opinion is heavily debated. This project proposes a descriptive framework for understanding the function of public opinion relating it to three of the main debates around the public and its place in democracy: 1) whether public opinion is most reliable as a continuous process of deliberation and exchange of ideas where people can learn from each other, or as a technical aggregation of people's opinions, such as voting or opinion polling, that clearly demarcates exactly what the majority wants; 2) whether public opinion should strive towards consensus and compromises between interested parties, or be a constant battleground between opposing ethico-political positions; 3) whether public opinion depends on high engagement by well-informed citizens, or is able to function relatively without demanding a lot of effort from the general public. These three debates have respectively been called voice versus aggregation, consensus versus agonism and engagement versus ignorance. Instead of taking any of the positions in the three debates, this project has proposed a framework, tentatively named the triaxial model, which has the purpose of highlighting the benefits and weaknesses of each of the six positions. The triaxial model serves as a lens through which the actual public opinion formation activities on social media can be examined rather than as a normative ideal to evaluate public opinion against.

Following the general framework of the triaxial model, communicative practices on social media and their effects with respect to political preferences and experiences of collectivity are reviewed. Social media communication is viewed as networked information flows containing strategic, journalistic, personal, social and algorithmic curation biases, which are centred on the political preferences of the individual user. Collectivity is thus best seen as personal action frames where collective action is an effect derived from the personally motivated pursuits of individuals rather than organized group efforts and as instances of momentary connectedness allowing people to come together in debate of protest, such as in a hashtag public, which is not necessarily experienced as a weak form of collectivity, but is potentially unsustainable if activities are not constantly reinitiated. The peculiarities of communication and collectivity on social media platforms are related back to the triaxial model through a review of recent theoretical concepts used in the context of social media publics, which includes the concepts: counter public, issue publics, networked publics, data publics, acclamation publics and affective publics. The most significant trait emphasized in this project, which is best explained with the concept of the data public, is the potential for social media to bridge the gap between voice and aggregation in the triaxial model. The affordances of most social media platforms are unrestricted enough that they allow for a lot of voice e.g. writing comments, but by simultaneously communicating with a central system, which is the platform that collects the data for all interactions, avenues are opened up towards ways of aggregating and measuring opinions. Furthermore, concepts such as acclamation publics and affective publics seem to emphasize social media's tendency towards agonism over consensus, while issue publics (or ad-hoc publics on social media) and counter publics on social media appear to somewhat favour ignorance over engagement.

Most social media platforms offer a variety of ways to communicate; one-to-one, one-to-many and many-to-many. As such it must be assumed that how the platforms are being utilized impacts the kind of role, they play in opinion formation. The main focus in this project is on the open public venues such as public pages on Facebook where most activity consists of varying degrees of interaction with and sharing of content and participation in comment threads. This builds on an assumption of everyday political engagement where users trade in and out of discussions, sometimes very quickly, without necessarily being on the lookout for political discussions in the first place. What people end up doing when they log onto their social media accounts, which is again influenced by strategic, journalistic, personal, social and algorithmic curation biases, has implications for whether opinion formation causes political polarization. In the networked information flows of social media, users can engage with political content that they find either agreeable or disagreeable. Coming across politically agreeable/disagreeable content can be both intentional and incidental. There are different benefits depending on either; engaging with content and other users who are aligned with one's own political preferences can bolster one's confidence and political identity, however no engagement with the opposite side, or disingenuous engagement where one seeks out the political opposition only to taunt or disturb, might lead to increased political polarization, especially if the effect is self-reinforcing, creating virtual echo-chambers. Again, while there are upsides and downsides to engagement with both politically agreeable and disagreeable information, it should be fair to assume that too much polarization and disconnection between politically opposite groups will be detrimental to the democratic function of public opinion. The methods designed in this project thus focus on finding patterns of behaviour in public social media spaces that relate to political homophily, political disagreement and the potential for cross-cutting agreement.

This project proposes a methodological framework that is informed by computational methods and Big Data practices. Big Data in the social sciences still being a fairly new area, there are few established methods. Most methodological literature has focused on general frameworks for working with large, or smaller, amounts of digitally source data. This thesis builds on the social analytics framework which describes the process of harvesting data using social media API's and then extracting structural, opinion and topical attributes from the behavioural data with the purpose of making a comprehensive analysis. Again, social analytics is a general frame to which much more specific methods need to be selected.

The empirical case chosen for testing specific methods of extracting insights about political homophily and potential polarization is the Danish public on Facebook, represented by a very large cross-section of public pages. The behavioural data, including all interactions by all users on the chosen pages, is downloaded via the Facebook API. Additionally, a survey is sent out to 3.000 Danes, which asks them about their political opinions and most importantly their current voting intention while also linking their answers with their Facebook profile. Based on the survey a prediction model is created with the purpose of inferring the voting intention of Danish Facebook users based on their behaviour on public pages. The model performs with an accuracy of 70% on a multiparty range and 99% on a left-right wing scale. The model reveals that positive reactions from users on posts made by politicians and political parties is a reasonably reliable indicator of voting intention.

Using voting intention as a proxy for political preference and building on the finding that positive reactions on political pages is a reliable estimator for it, the project presents a series of methods for calculating political homophily and agreement/disagreement in multiple steps of a discussion. Because it is near impossible to obtain a ground truth against which to test the reliability of the methods, it is instead tested against a set of common-sense assumptions such as: discussions about political issues are likely to have more political disagreement. The results yielded by the methods are shown to be non-random with respect to political behaviour.

In order to consider complex distributions of political homophily and polarization in the Danish public on Facebook, additional methods are proposed with the purpose of segmenting discussions based on the types of spaces in which they occur, the topics being discussed and the sentiments in the language. This entails manually labelling different public pages with an appropriate category based on domain knowledge and previous literature. Furthermore, a dictionary-based language model is created to automatically label Facebook posts with one of 17 topics based on the prevalence of certain words being used. Lastly, a prediction model based on machine learning is created with the purpose of being able to automatically sort Danish language text into two groups: those that employ harsh language and those that do not.

The automation aspect inherent in computational methods allow for all the methods developed to be used on any post in the Danish public that has a minimum of participating users. This is used to study broad trends of political homophily, disagreement and cross-cutting agreement in the Danish public on Facebook over time, with respect to sentiment, across different spaces and topics and in multiple steps. The main results reveal that political homophily and polarization is overall not increasing or decreasing over time, which is an important contribution to the debate about whether the curation biases on social media are inevitably causing increased polarization. It provides a counter narrative to research claiming that polarization is rife on social media. Instead homophily and heavy political disagreement appear to be strongly moderated by topics relating to immigration and refugees and spaces belonging to populist advocates. Although, there is some indication that the longer a discussion is active homophily and disagreement does appear to increase on average within that single discussion. Furthermore, political discussions that take place in spaces that are not created for political debate seem to increase the likelihood of fostering cross-cutting agreement, even if the issues being discussed are of a political nature, which is in line with previous research into “third spaces” on social media.

The methods developed in this project are well-posed to take advantage of social media’s unique position to bridge the gap between voice and aggregation. People can “freely” voice their opinions and insights based on their previous behaviour on the platform can be leveraged in order to create more transparency about the underlying biases that affect the resulting public opinion. Potentially this can produce agency in the data public and potentially greater control over configurations of the public with respect to consensus versus agonism and engagement versus ignorance.

Limitations

This project has proposed a useful theoretical framework for understanding the function of public opinion on social media and designed methods that can reliably leverage opinion with respect to political homophily and polarization, however there are still many theoretical and empirical limitations. Public opinion is a notoriously broad and fuzzy concept. The theoretical framework in this project builds on the public sphere tradition from media studies which omits many aspects of public opinion, especially those studied in the fields of political communication and political economy. Thus, the flow of opinion from informal publics to formal publics and its impact on democratic decision making in society is heavily under theorized. How participation in opinion formation on social media impacts the individual is covered, but focusing mainly political homophily, disagreement and polarization. The more general impact that political engagement on social media has on an individual with regard to identity, citizenship and continuous behaviour is only mentioned briefly. The real importance of the role of public opinion can be made clearer if a full synthesis between micro, meso and macro levels is theorized. This thesis has focused on the meso level consisting of small and large groups of people who come together, which connects strongly with the empirical case, at the cost of under theorizing the micro and macro levels. Still, achieving a greater understanding of opinion formation processes as they take place on posts on public Facebook pages is a useful contribution to further work on the function of the public across multiple levels, albeit insufficient on its own.

An inherent problem with public opinion on social media is the complexity of information flows. This project has reviewed some of the main characteristics of social media such as media convergence user generated content/user interaction and mediatization/personalization as well as having presented an overall frame which is best described as networked information flows centred on the political preferences of individual users and influenced by strategic, journalistic, personal, social and algorithmic curation biases. However, none of the concepts (i.e. the different curation biases) are examined in greater detail, which makes it difficult to relate them directly to the empirical case, which focuses only on public Facebook pages. Instead it has to simply be assumed that the biases present in the general information flow on social media also affect how users find, share and engage with content on public Facebook pages.

The project represents an attempt to further our understanding of public opinion on social media with respect to political polarization. The methods developed can be used to study general trends of polarization, but also to zoom in on a single Facebook post and get an estimate for how much political homophily, disagreement and cross-cutting agreement it elicits. However, the methods deliver only an estimate and not a complete representation of reality, as such, using the methods to find and study single discussions should only be seen as a way to guide further in-depth analysis. Rather the methods can be used to view public discussions in a new light and potentially point towards new ways of imagining the public

The empirical case in itself covers only a very small corner of all social media activity. It is limited to only public Facebook pages from Denmark. The results concerning levels of political homophily and polarization pertain only to Denmark, though they are still relevant inputs in the discussion of political communication on social media e.g. whether social media inevitably leads towards increased polarization or not. The results presented provide additional insights to the forces that can influence the increase and decrease of political polarization. However, the methods for measuring public opinion have been developed to be fairly generalizable, which means that it is technically possible to apply almost the same methods to multiple platforms given appropriate resources and access to data. A fruitful venue for future work would be to use some of the methods presented here to make a comparison between different countries.

As mentioned in the methodology chapter the current position for researchers is precarious at best. The results in this thesis cannot be replicated unless Facebook changes their general data policies, or a researcher gains privileged access. Terms of access are given by the data brokers on which most academic scholars have little influence.

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Appendices

Appendix 4.0-SI – Facebook Data

Table. Facebook Data Overview

DATA COLLECTION	FACEBOOK LEVEL	NUMBER OF ROWS
UNION	pages	84
UNION	posts	115650
UNION	comments	776821
UNION	replies	243403
UNION	post likes	6319444
UNION	comment likes	852941
UNION	reply likes	124549
POLITICAL	pages	1840
POLITICAL	posts	1201965
POLITICAL	comments	15548192
POLITICAL	replies	7284611
POLITICAL	post likes	82221948
POLITICAL	comment likes	17819941
POLITICAL	reply likes	6354957
LOCAL	pages	4211
LOCAL	posts	1035922
LOCAL	comments	6786830
LOCAL	replies	872287
LOCAL	post likes	44736249
LOCAL	comment likes	3454777
LOCAL	reply likes	545717
ORGANISATION	pages	4582
ORGANISATION	posts	301102
ORGANISATION	comments	7432863
ORGANISATION	replies	1531264
ORGANISATION	post likes	24422039
ORGANISATION	comment likes	2263026
ORGANISATION	reply likes	770503
MEDIA	pages	194
MEDIA	posts	2165588

MEDIA	comments	79190981
MEDIA	replies	40476169
MEDIA	post likes	244700745
MEDIA	comment likes	81907090
MEDIA	reply likes	21671772
TOTAL	Rows	703140257

Appendix 4.1-SI – Facebook Data Structures

Table. Facebook Data Variables

FACEBOOK DATA LEVEL	VARIABLE	DESCRIPTION
POST	Time Created	Timestamp for the publication of the content
POST	Headline	Headline for the post
POST	Description	The description below the headline
POST	Message	The main text content for the post
POST	Link	The attached link
POST	LIKE	The number of like emoji responses
POST	ANGRY	The number of angry emoji responses
POST	SAD	The number of sad emoji responses
POST	WOW	The number of wow emoji responses
POST	HAHA	The number of haha emoji responses
POST	LOVE	The number of love emoji responses
POST	Created on Page	The public page where the post was originally posted
POST	Post ID	The unique ID of the post
COMMENT	Time Created	Timestamp for the publication of the content
COMMENT	Message	The main text content for the comment
COMMENT	Created By	The anonymous user ID for the user who posted the content
COMMENT	LIKE	The number of like emoji responses
COMMENT	LOVE	The number of love emoji responses
COMMENT	Comment ID	The unique ID of the comment
COMMENT	Post ID	The unique ID of the post to which the comment was made
REPLY	Time Created	Timestamp for the publication of the content
REPLY	Message	The main text content for the reply
REPLY	Created By	The anonymous user ID for the user who posted the content
REPLY	LIKE	The number of like emoji responses
REPLY	LOVE	The number of love emoji responses
REPLY	Reply ID	The unique ID of the reply

REPLY	Comment ID	The unique ID of the comment to which the reply was made
POST LIKE	Made By	The anonymous user ID for the user who made the emoji response
POST LIKE	Post ID	The unique ID of the post to which the emoji response was made
COMMENT LIKE	Made By	The anonymous user ID for the user who made the LIKE/LOVE response
COMMENT LIKE	Comment ID	The unique ID of the comment to which the emoji response was made
REPLY LIKE	Made By	The anonymous user ID for the user who made the LIKE/LOVE response
REPLY LIKE	Reply ID	The unique ID of the reply to which the emoji response was made

Appendix 5.0-SI – Survey and Sample Sizes

Table. Data filtering and sample sizes for survey

Filter	Sample size
No filter, all respondents in survey	3050
Only respondents who reported their public Facebook ID in survey	1216
Only respondents who had liked at least one post on political pages corresponding to a party in parliament *(used in baseline and **models** II – III)*	659
Only respondents who had liked at least 7 posts on political pages *(used in model IV)*	468

Appendix 5.1-SI: Non-response analysis

In order to address the significant decrease in sample size from the full survey to the samples being used in our models, we have conducted a non-response analysis. The primary reduction in respondent numbers consists of individuals who did not have a Facebook profile or would not allow access to their public ID (N = 3050 – 1834 = 1216).

Accounting for most of the dropouts are the 40% of the Danish population who do not have a Facebook account. We also expected privacy concerns to reduce participant numbers. The second dropout category is comprised of respondents who would not vote for one of the nine parties or did not enter at least one political like during the period (N = 1216 – 557 = 659). Accounting for the majority of these dropouts are people who did not plan to vote or who were not among the 28% (1.3 million) of Danes who liked political actors.

In order to determine the extent of skewedness for survey features, we did a 10,000-fold permutation test of chi-square (X^2) scores for each of the samples (see Table S4). The first test compares the distribution of answers from two random samples both from the full survey (total survey N = 3050). The next compares random samples where one is from the full survey and the other from a sample of only respondents with attached Facebook profiles (on Facebook N = 1216). The last compares random samples where one is from the full survey and the other from a sample of only respondents with at least one political like on any of the parties in parliament (with political like N = 659). The distribution of answers corresponding to a single feature, such as age, is only considered to be skewed if the mean of the X^2 value, resulting from the permutation test, lies outside of the 95% confidence interval of the first permutation test that compared two random samples from the full survey. For example, in the N = 1216 sample, gender has an X^2 mean of 0.96, but the 95% confidence interval of N = 3050 has X^2 values between 0 and 3.5, so the skew is not significant. However, the N = 659 has a gender X^2 mean of 4.49, and is therefore considered to have a small skew. Whether a skew is small or large is determined by the relative skew from the largest to the smallest. It is important to remember that the degree of skew for a single feature is determined by its relation to *statistical* significance and not how skewed it is in the real world. For example, the most skewed feature, age, has a 10-percentage point difference between young and old.

Table. Population and sample distributions for base demographics[35]

[35] Source for population percentages: http://danmarksstatistik.dk/da/Statistik

CATEGORY	POPULATION	N = 1216	N = 659
FEMALE	0.5025	0.5444	0.5842
MALE	0.4975	0.4556	0.4158
AGE 18-34	0.2975	0.3497	0.3338
AGE 35-53	0.358	0.3765	0.3849
AGE 54-74	0.3445	0.2738	0.2813
REGION CAPITAL	0.3136	0.3519	0.3493
REGION CENTRAL JUTLAND	0.2267	0.216	0.2287
REGION NORTHERN JUTLAND	0.1024	0.0984	0.0943
REGION ZEALAND	0.1451	0.1005	0.1005
REGION SOUTHERN DENMARK	0.2122	0.2332	0.2272
STANDARD HIGH SCHOOL	0.1012	0.1278	0.1364
VOCATIONAL	0.3288	0.2393	0.2374
PH.D	0.0066	0.0151	0.0101
PRIMARY SCHOOL	0.2861	0.1708	0.1724
HIGHER EDUCATION (2-4½ YEARS)	0.1447	0.2194	0.2232
HIGHER EDUCATION (5 YEARS OR MORE)	0.0849	0.1661	0.1616
HIGHER EDUCATION (2 YEARS OR LESS)	0.0477	0.0616	0.0589

Table. Population and sample distributions compared

CATEGORY	N = 1216 COMPARED TO POPULATION	N = 659 COMPARED TO POPULATION
FEMALE	0.0419	0.0818
MALE	-0.0419	-0.0818
AGE 18-34	0.0523	0.0364
AGE 35-53	0.0185	0.0269
AGE 54-74	-0.0707	-0.0632
REGION CAPITAL	0.0383	0.0357
REGION CENTRAL JUTLAND	-0.0107	0.002
REGION NORTHERN JUTLAND	-0.004	-0.0081
REGION ZEALAND	-0.0446	-0.0446
REGION SOUTHERN DENMARK	0.0209	0.015
STANDARD HIGH SCHOOL	0.0265	0.0351
VOCATIONAL	-0.0896	-0.0914
PH.D	0.0085	0.0035
PRIMARY SCHOOL	-0.1153	-0.1137
HIGHER EDUCATION (2-4½ YEARS)	0.0747	0.0786
HIGHER EDUCATION (5 YEARS OR MORE)	0.0812	0.0768
HIGHER EDUCATION (2 YEARS OR LESS)	0.0138	0.0112

Table. Results of non-response chi-squared permutation tests

	Total survey (N = 3050)			With Facebook ID (N= 1216)			With political likes (N = 659)			Degree of skew	
Category	X^2 mean	0.025 quantile	0.975 quantile	X^2 mean	0.025 quantile	0.975 quantile	X^2 mean	0.025 quantile	0.975 quantile	N = 1216	N = 659
Party choice	8.08	3.11	15.23	17.42	9.81	27.67	19.91	9.92	29.24	Small	Small
Individual responsibility vs. Public responsibility	2.78	0.32	7.55	6.69	2.03	13.38	14.89	6.83	24.62	Not significant	Medium
Losing entitlement vs. Right to choose job	2.80	0.30	7.92	7.11	2.35	13.17	7.92	2.70	15.42	Not significant	Not significant
Social security reforms have become excessive vs. Just enough	2.80	0.38	7.51	3.38	0.67	7.61	6.08	1.86	12.94	Not significant	Not significant
Competition is healthy vs. Unhealthy	2.83	0.34	8.03	6.84	2.08	13.25	3.76	0.62	8.76	Not significant	Not significant
More freedom for corporations vs. Less freedom	2.87	0.31	7.85	1.95	0.23	5.05	5.90	1.53	12.61	Not significant	Not significant
People with high incomes do not pay enough taxes	2.81	0.34	7.33	4.21	0.85	9.20	7.00	2.06	14.19	Not significant	Not significant
Income inequality is too high	2.69	0.37	7.36	3.62	0.72	8.33	4.08	0.96	9.12	Not significant	Not significant
Violent criminals should face more severe punishment	2.79	0.32	7.37	1.89	0.22	5.17	2.63	0.38	7.23	Not significant	Not significant
More border control is desirable	2.85	0.38	7.80	6.97	2.21	13.87	7.83	2.50	15.09	Not significant	Not significant
We should do more to protect national heritage	2.82	0.33	7.81	5.81	1.61	11.62	6.63	2.12	13.67	Not significant	Not significant
We should prevent crime through counseling rather than punishment	2.79	0.38	7.79	6.06	1.71	12.27	6.84	2.02	13.55	Not significant	Not significant
Environment vs. Corporate growth	2.93	0.44	8.04	4.57	1.17	9.89	8.34	2.83	15.48	Not significant	Small
Homosexuals should have exactly the same rights as everyone else	2.71	0.32	7.70	7.95	2.84	14.19	8.32	2.94	15.62	Small	Small
Higher taxes on gasoline are desirable	2.91	0.37	7.82	9.44	3.80	17.21	7.38	2.46	14.30	Small	Not significant
Religious extremists have the right to freedom of public assembly	2.82	0.38	7.58	8.49	3.02	16.02	7.65	2.44	15.36	Small	Small
Gender	0.65	0	3.52	0.97	0	3.78	4.49	0.71	10.46	Not significant	Small
Age	1.33	0.03	4.59	27.09	16.69	39.90	14.59	6.75	25.87	Large	Medium
Geography	2.72	0.30	7.42	3.29	0.63	7.46	4.05	0.84	9.18	Not significant	Not significant
Education	5.53	1.46	12.54	16.98	6.62	28.92	24.74	14.84	36.18	Small	Small

Appendix 5.2-SI: Regression Models and Evaluation Metrics

All data analysis was carried out via Python. The code used for the regression models can be attributed mainly to Turi's GraphLab Create[36]; all other data analysis is original code. All data models are based on GraphLab Create's Logistic Regression module and implement only L1 regularization (L2 is set to 0). L1 regularization is used for selecting the coefficients corresponding to the features that deliver the best bias–variance tradeoff for generalizing the model. L1 regularization performs this selection by setting least important coefficients to exactly zero while decreasing other coefficients by a value relative to the chosen λ-value. The least important coefficients can roughly be defined as those least related to (least correlated with) the maximum log likelihood (MLE) of the model under a certain λ-value. The relation between the MLE and a given coefficient is determined by soft thresholding [34,35].

We report the following evaluative measures, all in the form of cross-validated averages:

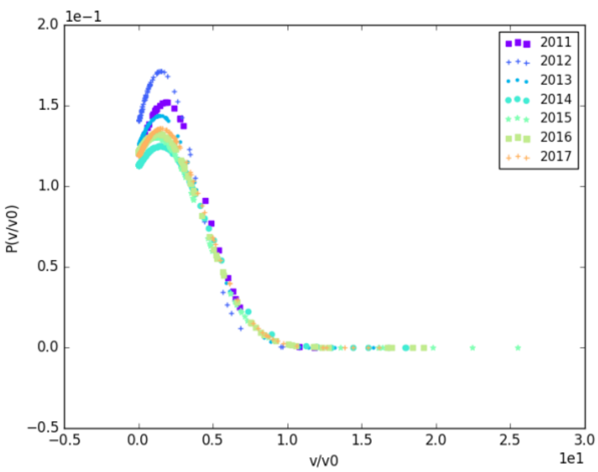
> **AUC (area under [receiver operating characteristic, or ROC] curve):** Effectively states overall ability of the regression model for separating classes based on input variables with 0.5 denoting no relationship between explanatory variables and prediction rate. The thresholds for the ROC curve are incremented by 0.0001.
>
> **Precision:** Number of true positives out of all positives, or TP/(TP + FP). In multiclass cases, precision is calculated as the mean of all classes.
>
> **Recall:** Number of true positives out of all positives and false negatives, TP/(TP + FN). In multiclass cases, recall is calculated as the mean of all classes.
>
> **Accuracy:** Global amount of correctly predicted classes divided by total sample size of the test data. In multiclass cases, this is not the mean of all class accuracies.

[36] See https://turi.com/products/create/docs/.

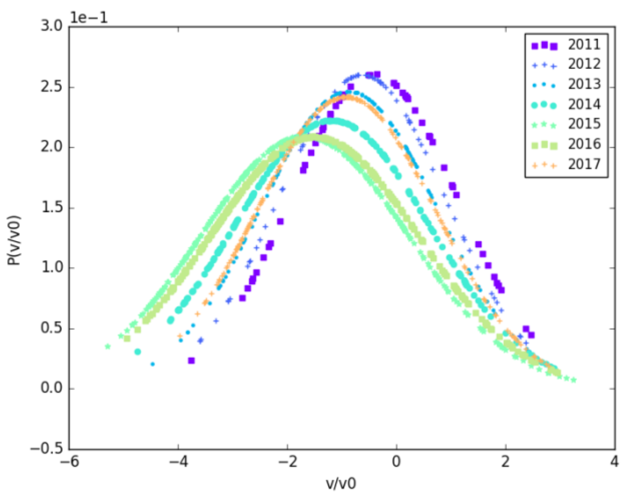
Appendix 5.3-SI: FC-Scaling

We have sought to further explore the relationship between what Facebook users like and what they vote by testing whether likes conform to the same universality scaling as that proposed by (Chatterjee et. al, 2013) and (Fortunato & Castellano, 2007), also known as FC-scaling. The main insight provided by studies into FC-scaling is that the distribution of votes among candidates in an election depends solely on the relationship between the votes received by a candidate and the average number of votes received by that candidates political party (V/V0). This means that the distribution is very similar across countries and years (for countries that have similar voting systems). Here we only have data from one country, Denmark, so we compare distributions for different years. We have sought to recreate the model proposed by (Chatterjee et. al, 2013) as accurately as possible with the only exception being that our model deals with Facebook likes entered on posts by candidates instead of votes received by candidates.

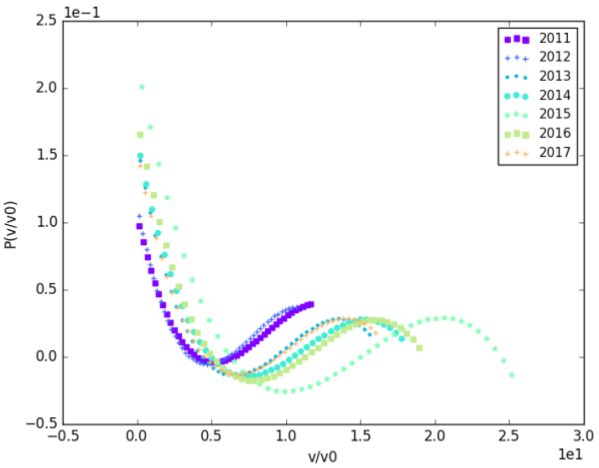
S5.3 Fig: FC-scaling for likes received by candidates on Facebook



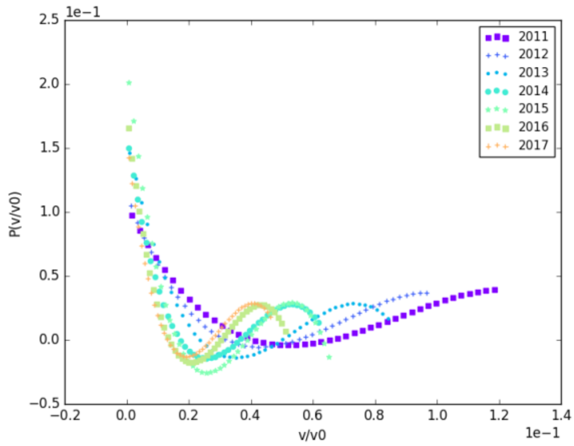
S5.3-A: Gaussian probability distribution of likes received by a candidate divided by the average number of votes received by candidates from her/his particular party.



S5.3-B: Gaussian probability distribution of the natural logarithm of likes received by a candidate divided by the average number of votes received by candidates from her/his particular party.



S5.3-C: Gaussian probability distribution of likes received by a candidate divided by the average number of votes received by candidates from her/his particular party. Presented as a histogram with 45 bins.



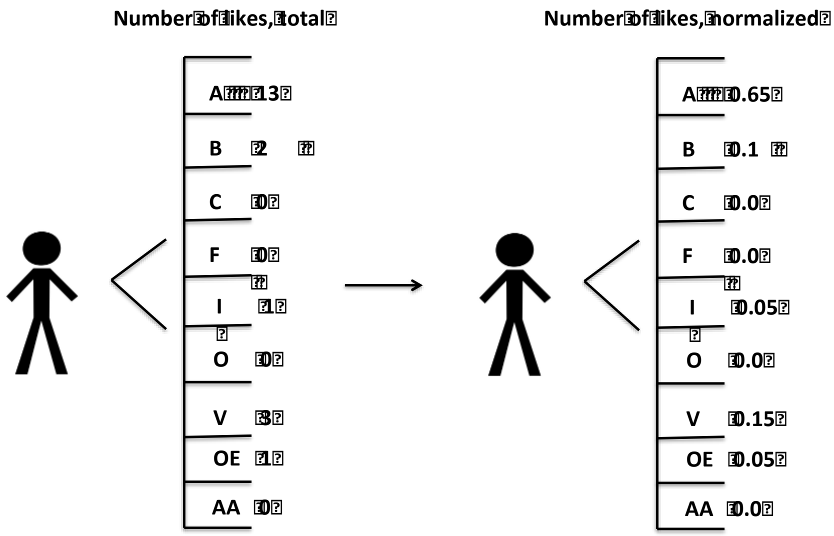
S5.3-D: Gaussian probability distribution of likes received by a candidate divided by the average number of votes received by candidates from her/his particular party. Presented as a histogram with 45 bins and both axes normalized (each

Two things we can note from the quick exploration is 1) likes seem to behave differently from votes in that there is a greater distance between candidates who receive the most likes and those who receive few likes i.o.w an exponentially increasing relationship; 2) the distributions for earlier years differ somewhat from those of later years. The reason for the second point is most likely that Facebook was much less popular in 2011, 2012 and 2013, meaning that the political landscape consisting of candidates and citizens was radically different.

Still the distributions are relatively similar across the different years, which suggests the existence of a mechanism related to the universality scaling found with votes received by candidates in real elections. However, this is the only part of the present study that looks at the relation between Facebook likes and votes at the *candidate level*. More research is needed to explore this aspect further.

Appendix 6.0-SI

User Vector, Normalized



Appendix 7.0: Topics for Dictionary Model

TOPIC	NWORDS
CLIMATE AND ENVIRONMENT	162
CULTURE	376
DOMESTIC POLICY	210
ECONOMY	198
EDUCATION AND RESEARCH	154
EMPLOYMENT AND THE LABOR MARKET	170
EVERYDAY LIFE AND CONSUMPTION	162
FOREIGN POLICY	133
GENDER EQUALITY, GENDER AND DISCRIMINATION	129
HEALTH	342
JUSTICE AND SECURITY POLICY	208
POLITICAL GAMES AND REFERENDUMS	132
REFUGEES AND INTEGRATION	120
RELIGION	99
SOCIAL POLICY	162
TECHNOLOGY AND DIGITALIZATION	77

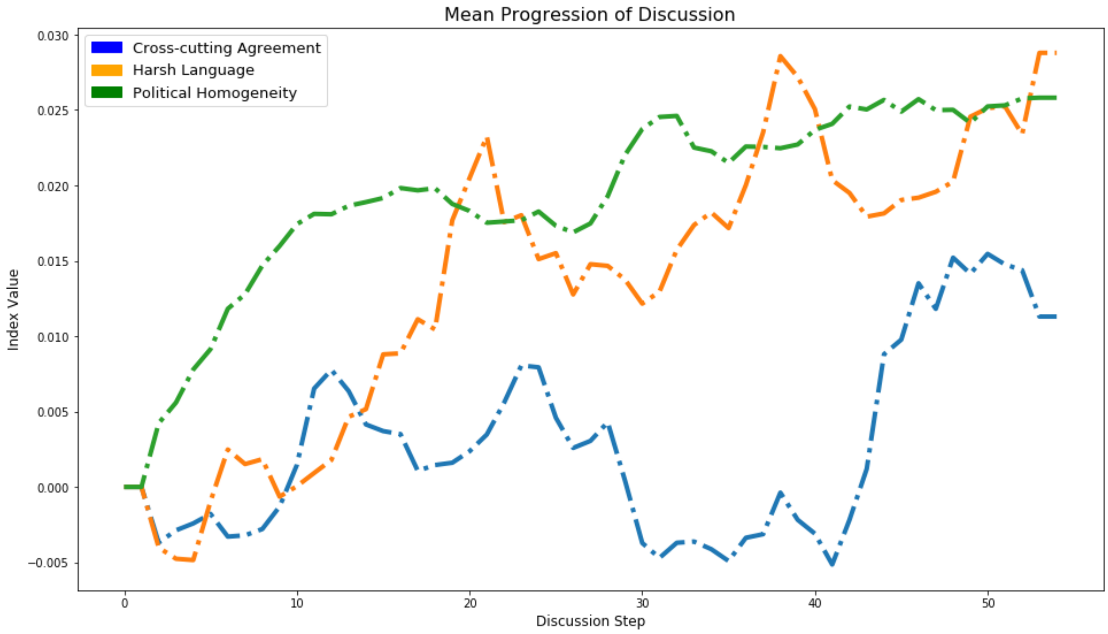
Appendix 8.0-SI: Variables Available for Analysis

VARIABLE CATEGORY	VARIABLE NAME	DESCRIPTION
BASE VARIABLE		
	datetime	The timestamp for when the content is published
	message_text	All the textual content of the post/comment/reply
	message_type	Whether the content belongs to a post, comment or reply
	content_type	If content is a post, this designates the type of post (e.g. picture or link)
	page_origin	The page where the content is posted
	link	The attached link of the content
	link_domain	The domain of the attached link
	by_id	The unique ID of the page / person who posted the content
	by_woman	1 = content is published by femal. 0 = content is published by male.
	reactions_total	Number of total reactions for the post / comment / reply
	comments_total	Number of comments for the content
	shares	Number of shares if content is a post
	sad_total	Number of sad reactions to the content
	angry_total	Number of angry reactions to the content
	like_total	Number of like reactions to the content
	love_total	Number of love reactions to the content
	women_reactions	Proportion of females who reacted to content. Range = 0 - 1.
	women_comments	Proportion of females who commented on content. Range = 0 - 1.
	gender_penetration	Proportion of reactions + comments for which the sex of the individual could reliably be ascertained
PAGE VARIABLES		
	entity_category	The category that a page belongs to. Changes depending on the debates from which the content originates (e.g. Political News if from the Media data collection)
TOPIC VARIABLES		
	topic	The topic that the content is most likely to belong to
	secondary_topic	The topic that the content is second most likely to belong to
	custom_category	Empty placeholder variable. Not used in this database.
POLITICAL VARIABLES		

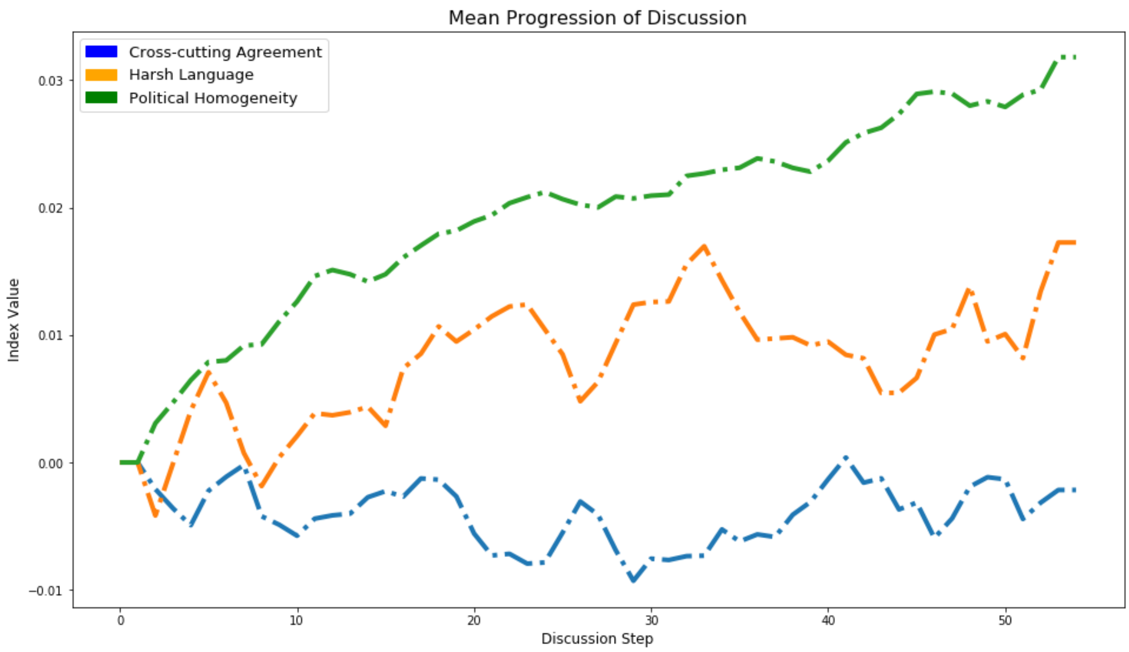
	by_party	The political party that the one who posted the content belongs to. If it's a person this variable designates that persons voting intention. If it's a politician this variable designates the party that she belongs to.
	pol_penetration	The proportion of reaction + comments for which the individuals' voting intention can reliably be determined.
	left_wing_reactions	The proportion of reactions that belong to people with the intention to vote for any left wing party.
	left_wing_comments	The proportion of comments that belong to people with the intention to vote for any left wing party.
	initial_disagree	The level of political disagreement for the content based on the way users react and comment on the content ((disCom + disAs) / 2).
	subsequent_agree (subAgree)	The level of subsequent political agreement based on the way people interact with each other within the comment thread.
	subsequent_agree_sin	The level of subsequent political agreement for a single comment or reply.
	initial_disagree_comagg	The level of political disagreement for the content based on the way users react and comment on the content. Aggregated one level down from the content. If the content is a post this variable designates the amount of political disagreement of all comments.
	subsequent_agree_comagg	The level of subsequent political agreement based on the way people interact with each other within the comment thread. Aggregated one level down from the content. If the content is a post this variable designates the amount of subsequent political of all comments.
	homogenity_reactions	The level of political homogeneity for the content based on all users who reacted
	homogenity_comments	The level of political homogeneity for the content based on all users who commented
	homogenity_all	The level of political homogeneity for the content based on all users who commented and/or reacted
SENTIMENT VARIABLES		
	hate_penetration	The proportion of comments to a piece of content for which harsh language use probability can reliably be determined.
	hate_probability	The probability that the content contains harsh language
	agg_hate_probability	The probability that all comments to the content contain harsh language.
META VARIABLES		
	message_id	The unique ID of the content

	mid_level_id	The unique ID of the parent to the content. If the content is a comment the parent is the post ID. If the content is a post the parent is the page it was published on.
	top_level_id	The top level parent of the content.
	link_to_message	The link to the specific piece of content on Facebook.
	from_db	The data collection that the content is part of (e.g. Local, Media, Political, Organization or Union)

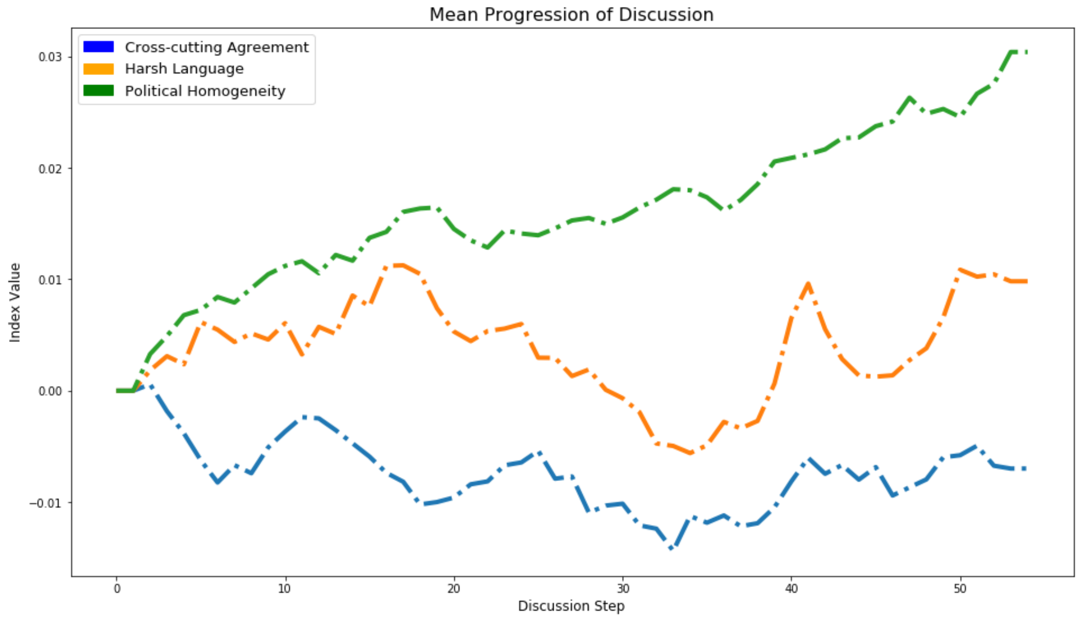
Appendix 8.2-SI Mean Progression of Discussion, Selected Topics



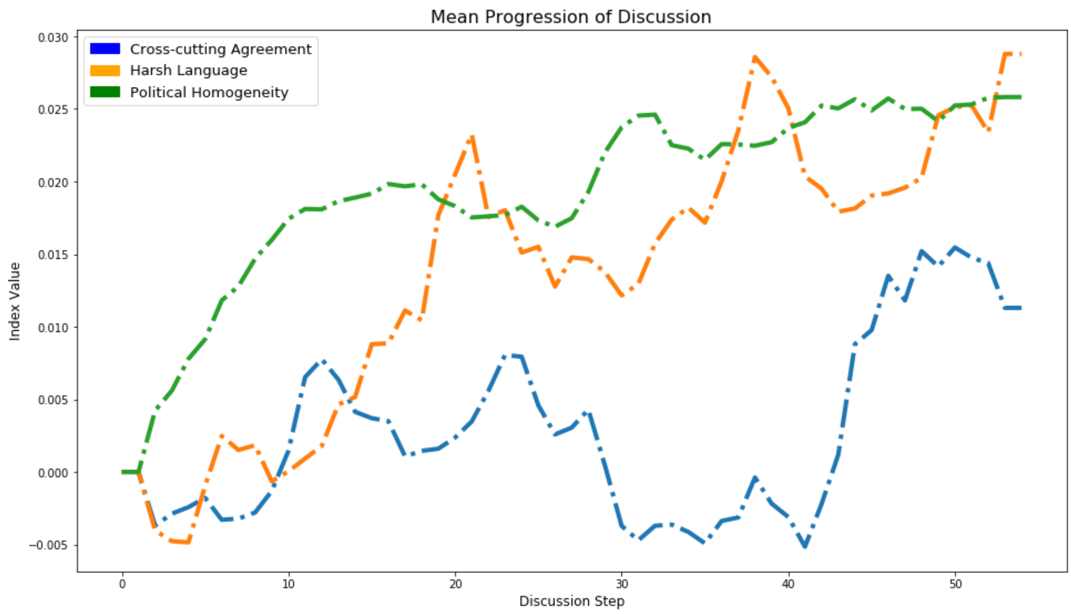
Topic: Economy



Topic: Employment and Labour Market



Topic: Social Policy



Topic: Domestic Policy

Appendix 8.3-SI Cross-cutting Agreement ~ *, Comments, Complex

DEP. VARIABLE:	CROSS_AGREEMEN	R-SQUARED:	0.139	
MODEL:	OLS	Adj. R-squared:	0.139	
METHOD:	Least Squares	F-statistic:	182.3	
DATE:	Sat	26 Oct 2019	Prob (F-statistic):	0.00
TIME:	20:59:49	Log-Likelihood:	1.3520e+05	
NO. OBSERVATIONS:	436239	AIC:	-2.696e+05	
DF RESIDUALS:	435851	BIC:	-2.654e+05	
DF MODEL:	387			
COVARIANCE TYPE:	nonrobust			
	coef	std err	t	P>|t|
MESSAGE_LEN	3.892e-09	1.61e-09	2.419	0.016
REFUGEES_AND_INTEGRATION	-0.1701	0.014	-12.398	0.000
TABLOID	0.0596	0.002	24.205	0.000
WOMEN_ALL	0.0064	0.003	2.457	0.014
POLITICIAN_V	-0.1137	0.003	-33.113	0.000
POLITICIAN_B	-0.1053	0.004	-24.122	0.000
POLITICAL_GAMES_AND_REFERENDUMS	-0.0610	0.019	-3.222	0.001
HEALTH	0.1612	0.019	8.418	0.000
HATE_PROBABILITY	-0.0086	0.003	-3.031	0.002
O	-0.0484	0.002	-19.386	0.000
A	0.0054	0.003	1.595	0.111
B	-0.0320	0.004	-8.038	0.000
POLITICAL NEWS	-0.0882	0.005	-18.228	0.000
RELIGION	-0.0200	0.009	-2.156	0.031
ECONOMY	-0.1203	0.026	-4.604	0.000
BY_WOMAN	-0.0031	0.001	-4.053	0.000

JUSTICE_AND_SECURITY_POLICY	0.2540	0.018	13.986	0.000
LOCAL NEWS	0.0376	0.003	13.000	0.000
C	0.0257	0.005	5.576	0.000
POLITICIAN_OE	-0.0730	0.003	-21.562	0.000
DEBATE	-0.0616	0.004	-17.174	0.000
POLITICIAN_F	-0.0537	0.003	-18.723	0.000
POLITICIAN_I	-0.0659	0.003	-21.979	0.000
I	-0.0327	0.003	-10.194	0.000
POLITICIAN_A	-0.0598	0.003	-19.630	0.000
FOREIGN_POLICY	0.0750	0.016	4.702	0.000
POLITICIAN_NB	-0.1698	0.009	-18.140	0.000
CULTURE	0.1551	0.016	9.628	0.000
SOCIAL_POLICY	-0.0521	0.019	-2.723	0.006
CLIMATE_AND_ENVIRONMENT	-0.0321	0.012	-2.681	0.007
SPORT	0.1064	0.006	16.553	0.000
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	0.0716	0.022	3.182	0.001
GENERAL NEWS	0.0088	0.001	5.898	0.000
TECHNOLOGY_AND_DIGITALIZATION	0.0950	0.009	10.877	0.000
WITH_LINK	-0.0206	0.003	-8.206	0.000
AA	0.0311	0.004	7.470	0.000
LIFESTYLE	0.0553	0.006	9.082	0.000
POLITICIAN_AA	-0.0704	0.004	-17.902	0.000
LO	0.0560	0.005	10.490	0.000

POLITICIAN_C	-0.0399	0.004	-9.852	0.000
EDUCATION_AND_RESEARCH	0.0441	0.012	3.621	0.000
NB	0.0163	0.008	2.123	0.034
OTHER	0.0036	0.004	0.969	0.332
V	-0.0115	0.003	-3.811	0.000
OE	-0.0127	0.002	-7.533	0.000
RIGHT LEANING NEWS	-0.0038	0.003	-1.276	0.202
LEFT LEANING NEWS	-0.0238	0.004	-6.652	0.000
EMPLOYMENT_AND_THE_LABOR_MARKET	-0.0841	0.015	-5.625	0.000
DOMESTIC_POLICY	0.0238	0.009	2.734	0.006
GENERAL NEWS*REFUGEES_AND_INTEGRATION	-0.2240	0.009	-23.584	0.000
O*REFUGEES_AND_INTEGRATION	-0.0202	0.015	-1.312	0.190
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION	0.1421	0.015	9.388	0.000
WOMEN_ALL*HEALTH	-0.0461	0.023	-2.042	0.041
GENERAL NEWS*HEALTH	0.1236	0.015	8.263	0.000
B*REFUGEES_AND_INTEGRATION	-0.0545	0.016	-3.328	0.001
WOMEN_ALL*POLITICAL_GAMES_AND_REFERENDUMS	-0.0484	0.035	-1.374	0.170
TABLOID*JUSTICE_AND_SECURITY_POLICY	-0.0076	0.015	-0.515	0.606
POLITICIAN_B*REFUGEES_AND_INTEGRATION	-0.0361	0.014	-2.633	0.008
TABLOID*HEALTH	-0.0205	0.024	-0.840	0.401
A*JUSTICE_AND_SECURITY_POLICY	-0.0797	0.019	-4.222	0.000
WOMEN_ALL*JUSTICE_AND_SECURITY_POLICY	-0.1375	0.015	-9.456	0.000
OE*REFUGEES_AND_INTEGRATION	0.0359	0.015	2.461	0.014

O*FOREIGN_POLICY	-0.1462	0.017	-8.573	0.000
O*RELIGION	0.0092	0.008	1.122	0.262
V*REFUGEES_AND_INTEGRATION	0.0403	0.016	2.478	0.013
WOMEN_ALL*RELIGION	-0.0653	0.012	-5.547	0.000
GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY	0.0821	0.012	6.842	0.000
POLITICAL NEWS*REFUGEES_AND_INTEGRATION	-0.1758	0.038	-4.672	0.000
HATE_PROBABILITY*RELIGION	0.0682	0.010	7.127	0.000
GENERAL NEWS*RELIGION	-0.1271	0.008	-15.245	0.000
B*RELIGION	0.0081	0.020	0.405	0.686
O*HEALTH	0.0114	0.022	0.528	0.597
HATE_PROBABILITY*ECONOMY	-0.1160	0.032	-3.588	0.000
GENERAL NEWS*POLITICAL_GAMES_AND_REFERENDUMS	-0.3302	0.024	-13.629	0.000
POLITICIAN_V*ECONOMY	0.0249	0.027	0.909	0.363
GENERAL NEWS*SOCIAL_POLICY	0.0859	0.016	5.276	0.000
WOMEN_ALL*SOCIAL_POLICY	0.1263	0.024	5.281	0.000
I*ECONOMY	-0.1549	0.029	-5.323	0.000
WOMEN_ALL*CULTURE	-0.1276	0.025	-5.166	0.000
BY_WOMAN*RELIGION	-0.0167	0.005	-3.186	0.001
WOMEN_ALL*ECONOMY	-0.0490	0.030	-1.638	0.101
POLITICIAN_B*POLITICAL_GAMES_AND_REFERENDUMS	0.2161	0.044	4.861	0.000
B*POLITICAL_GAMES_AND_REFERENDUMS	0.0312	0.034	0.906	0.365
V*HEALTH	0.1038	0.024	4.404	0.000
TABLOID*EMPLOYMENT_AND_THE_LABOR_MARKET	0.0893	0.022	4.094	0.000

GENERAL NEWS*CULTURE	0.0780	0.014	5.528	0.000
V*POLITICAL_GAMES_AND_REFERENDUMS	-0.2054	0.029	-7.195	0.000
POLITICIAN_I*ECONOMY	0.0514	0.028	1.864	0.062
POLITICIAN_V*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.0192	0.032	-0.591	0.554
POLITICIAN_A*ECONOMY	-0.0917	0.033	-2.783	0.005
POLITICIAN_V*DOMESTIC_POLICY	0.0272	0.021	1.317	0.188
OTHER*REFUGEES_AND_INTEGRATION	-0.4723	0.035	-13.616	0.000
POLITICIAN_F*REFUGEES_AND_INTEGRATION	0.0178	0.017	1.034	0.301
A*HEALTH	-0.0905	0.018	-4.975	0.000
GENERAL NEWS*DOMESTIC_POLICY	0.0688	0.014	5.003	0.000
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT	-0.2920	0.076	-3.860	0.000
OE*ECONOMY	0.0808	0.028	2.926	0.003
OE*JUSTICE_AND_SECURITY_POLICY	-0.0646	0.022	-2.954	0.003
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET	0.0249	0.017	1.439	0.150
A*ECONOMY	-0.0161	0.027	-0.596	0.551
OE*RELIGION	0.0034	0.011	0.316	0.752
A*POLITICAL_GAMES_AND_REFERENDUMS	-0.1576	0.026	-5.994	0.000
O*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1414	0.018	7.862	0.000
V*SOCIAL_POLICY	0.0676	0.024	2.869	0.004
GENERAL NEWS*FOREIGN_POLICY	-0.1439	0.016	-8.807	0.000
POLITICIAN_B*ECONOMY	0.3135	0.056	5.562	0.000
AA*REFUGEES_AND_INTEGRATION	0.0462	0.019	2.492	0.013
V*CLIMATE_AND_ENVIRONMENT	-0.1606	0.034	-4.757	0.000

DEBATE*RELIGION	-0.1698	0.028	-6.155	0.000
WOMEN_ALL*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	-0.1800	0.042	-4.298	0.000
POLITICIAN_V*FOREIGN_POLICY	-0.0100	0.045	-0.223	0.824
TABLOID*ECONOMY	0.1283	0.033	3.885	0.000
AA*JUSTICE_AND_SECURITY_POLICY	-0.1141	0.025	-4.557	0.000
TABLOID*REFUGEES_AND_INTEGRATION	-0.1517	0.015	-10.174	0.000
POLITICIAN_OE*POLITICAL_GAMES_AND_REFERENDUMS	0.1420	0.039	3.644	0.000
O*SOCIAL_POLICY	0.0113	0.016	0.697	0.486
OTHER*POLITICAL_GAMES_AND_REFERENDUMS	-0.7440	0.103	-7.226	0.000
C*DOMESTIC_POLICY	0.1328	0.035	3.840	0.000
POLITICIAN_F*DOMESTIC_POLICY	-0.0743	0.030	-2.445	0.015
V*ECONOMY	0.0053	0.032	0.163	0.870
POLITICIAN_OE*JUSTICE_AND_SECURITY_POLICY	-0.0891	0.032	-2.801	0.005
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY	0.2241	0.029	7.697	0.000
C*JUSTICE_AND_SECURITY_POLICY	-0.2694	0.029	-9.399	0.000
POLITICIAN_V*RELIGION	0.0488	0.011	4.524	0.000
LOCAL NEWS*REFUGEES_AND_INTEGRATION	-0.2057	0.016	-12.544	0.000
V*JUSTICE_AND_SECURITY_POLICY	-0.1580	0.019	-8.280	0.000
HATE_PROBABILITY*JUSTICE_AND_SECURITY_POLICY	0.0926	0.013	7.086	0.000
AA*HEALTH	-0.0898	0.023	-3.889	0.000
AA*CLIMATE_AND_ENVIRONMENT	-0.0746	0.029	-2.570	0.010
POLITICIAN_NB*JUSTICE_AND_SECURITY_POLICY	0.3609	0.086	4.195	0.000
A*RELIGION	0.0683	0.015	4.583	0.000

POLITICIAN_V*HEALTH	-0.0231	0.041	-0.559	0.576
NB*HEALTH	0.3407	0.097	3.530	0.000
DEBATE*POLITICAL_GAMES_AND_REFERENDUMS	0.3537	0.062	5.726	0.000
A*SOCIAL_POLICY	-0.0294	0.018	-1.666	0.096
POLITICIAN_C*CLIMATE_AND_ENVIRONMENT	-0.3110	0.044	-7.079	0.000
LOCAL NEWS*ECONOMY	0.2169	0.056	3.879	0.000
POLITICIAN_C*TECHNOLOGY_AND_DIGITALIZATION	-0.7910	0.097	-8.169	0.000
OE*CULTURE	0.0609	0.021	2.914	0.004
V*FOREIGN_POLICY	-0.0672	0.026	-2.612	0.009
V*EDUCATION_AND_RESEARCH	0.1570	0.030	5.280	0.000
POLITICIAN_NB*RELIGION	0.1046	0.027	3.922	0.000
POLITICAL NEWS*ECONOMY	0.1293	0.049	2.660	0.008
POLITICIAN_OE*EMPLOYMENT_AND_THE_LABOR_MARKET	0.0838	0.026	3.285	0.001
POLITICIAN_I*FOREIGN_POLICY	-0.2409	0.061	-3.919	0.000
POLITICIAN_B*FOREIGN_POLICY	0.1485	0.045	3.273	0.001
LEFT LEANING NEWS*REFUGEES_AND_INTEGRATION	-0.0826	0.029	-2.864	0.004
POLITICIAN_A*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1379	0.029	4.799	0.000
I*RELIGION	0.1039	0.017	6.201	0.000
OE*DOMESTIC_POLICY	-0.0424	0.014	-3.010	0.003
I*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.0782	0.025	-3.153	0.002
POLITICIAN_C*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.1416	0.069	-2.062	0.039
C*RELIGION	0.0925	0.019	4.852	0.000
POLITICAL NEWS*DOMESTIC_POLICY	0.0919	0.047	1.943	0.052

NB*REFUGEES_AND_INTEGRATION	-0.1229	0.033	-3.725	0.000
O*JUSTICE_AND_SECURITY_POLICY	-0.1896	0.018	-10.688	0.000
I*CLIMATE_AND_ENVIRONMENT	-0.0366	0.034	-1.071	0.284
POLITICIAN_V*TECHNOLOGY_AND_DIGITALIZATION	0.2885	0.038	7.527	0.000
C*CLIMATE_AND_ENVIRONMENT	0.1826	0.046	3.967	0.000
B*JUSTICE_AND_SECURITY_POLICY	-0.0756	0.021	-3.606	0.000
RIGHT LEANING NEWS*CLIMATE_AND_ENVIRONMENT	-0.3873	0.079	-4.876	0.000
POLITICIAN_C*FOREIGN_POLICY	-0.2356	0.108	-2.172	0.030
NB*ECONOMY	0.6126	0.106	5.786	0.000
AA*ECONOMY	0.0726	0.031	2.349	0.019
NB*EMPLOYMENT_AND_THE_LABOR_MARKET	0.3949	0.109	3.624	0.000
OTHER*CULTURE	-0.2724	0.101	-2.687	0.007
B*HEALTH	0.0790	0.024	3.236	0.001
NB*JUSTICE_AND_SECURITY_POLICY	-0.2525	0.040	-6.257	0.000
A*REFUGEES_AND_INTEGRATION	0.2089	0.015	13.644	0.000
V*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1511	0.024	6.368	0.000
POLITICIAN_C*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	-0.5127	0.130	-3.940	0.000
TABLOID*RELIGION	-0.1595	0.009	-17.809	0.000
AA*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1084	0.028	3.919	0.000
HATE_PROBABILITY*DOMESTIC_POLICY	0.0751	0.021	3.634	0.000
B*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1803	0.035	5.122	0.000
RIGHT LEANING NEWS*ECONOMY	-0.0053	0.037	-0.145	0.885
DEBATE*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1065	0.054	1.955	0.051

O*EDUCATION_AND_RESEARCH	0.1971	0.030	6.553	0.000
TABLOID*POLITICAL_GAMES_AND_REFERENDUMS	-0.2130	0.046	-4.641	0.000
RIGHT LEANING NEWS*HEALTH	-0.0886	0.044	-2.029	0.042
DEBATE*HEALTH	0.6201	0.090	6.895	0.000
DEBATE*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	0.2809	0.071	3.932	0.000
AA*DOMESTIC_POLICY	-0.0692	0.020	-3.432	0.001
LOCAL NEWS*RELIGION	-0.2313	0.031	-7.361	0.000
POLITICAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET	0.4112	0.066	6.264	0.000
HATE_PROBABILITY*EMPLOYMENT_AND_THE_LABOR_MARKET	0.0959	0.024	4.050	0.000
OTHER*SOCIAL_POLICY	0.2598	0.088	2.952	0.003
NB*FOREIGN_POLICY	-0.2921	0.070	-4.165	0.000
OTHER*DOMESTIC_POLICY	0.3180	0.068	4.644	0.000
B*TECHNOLOGY_AND_DIGITALIZATION	0.1193	0.035	3.429	0.001
DEBATE*JUSTICE_AND_SECURITY_POLICY	0.2972	0.063	4.712	0.000
O*ECONOMY	0.2894	0.041	7.101	0.000
RIGHT LEANING NEWS*REFUGEES_AND_INTEGRATION	0.1294	0.016	7.982	0.000
POLITICIAN_A*RELIGION	0.0590	0.019	3.100	0.002
DEBATE*EDUCATION_AND_RESEARCH	0.4449	0.085	5.250	0.000
OE*FOREIGN_POLICY	0.1692	0.025	6.847	0.000
B*SOCIAL_POLICY	0.1039	0.029	3.568	0.000
O*CLIMATE_AND_ENVIRONMENT	0.2473	0.031	8.099	0.000
POLITICIAN_AA*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1267	0.046	2.749	0.006
TABLOID*FOREIGN_POLICY	-0.2176	0.028	-7.907	0.000

WITH_LINK*FOREIGN_POLICY	0.2175	0.054	4.029	0.000
GENERAL NEWS*ECONOMY	-0.0046	0.020	-0.230	0.818
POLITICIAN_C*JUSTICE_AND_SECURITY_POLICY	0.0575	0.025	2.269	0.023
POLITICAL NEWS*HEALTH	0.5249	0.092	5.705	0.000
I*REFUGEES_AND_INTEGRATION	0.1951	0.019	10.186	0.000
DEBATE*TECHNOLOGY_AND_DIGITALIZATION	0.4337	0.113	3.828	0.000
DEBATE*SOCIAL_POLICY	0.2897	0.077	3.757	0.000
POLITICIAN_A*EDUCATION_AND_RESEARCH	0.1595	0.040	4.022	0.000
POLITICIAN_NB*HEALTH	1.0934	0.263	4.155	0.000
RIGHT LEANING NEWS*DOMESTIC_POLICY	-0.0373	0.029	-1.300	0.194
HATE_PROBABILITY*O	-0.0614	0.003	-21.172	0.000
TABLOID*A	0.0163	0.003	4.977	0.000
WOMEN_ALL*I	0.1292	0.005	26.923	0.000
TABLOID*OE	0.0372	0.003	12.145	0.000
WOMEN_ALL*A	-0.0077	0.004	-2.036	0.042
POLITICIAN_B*O	-0.1125	0.007	-15.376	0.000
GENERAL NEWS*I	0.0211	0.003	7.953	0.000
HATE_PROBABILITY*B	-0.0331	0.005	-7.058	0.000
WOMEN_ALL*C	0.0798	0.008	10.599	0.000
GENERAL NEWS*A	0.0152	0.003	5.504	0.000
HATE_PROBABILITY*A	0.0022	0.005	0.449	0.653
POLITICIAN_V*OE	-0.0829	0.007	-11.709	0.000
WOMEN_ALL*B	0.0185	0.005	3.587	0.000

POLITICIAN_V*O	0.0559	0.004	12.915	0.000
POLITICIAN_V*A	-0.0493	0.007	-7.422	0.000
POLITICIAN_V*B	-0.0820	0.008	-9.795	0.000
POLITICIAN_B*V	-0.1098	0.009	-12.475	0.000
WOMEN_ALL*V	0.0778	0.004	18.977	0.000
TABLOID*AA	0.0209	0.005	3.838	0.000
GENERAL NEWS*B	-0.0118	0.003	-4.340	0.000
POLITICAL NEWS*OE	-0.0582	0.008	-7.451	0.000
RIGHT LEANING NEWS*A	0.0930	0.006	15.034	0.000
LOCAL NEWS*A	0.0346	0.005	7.086	0.000
TABLOID*V	-0.0482	0.003	-15.875	0.000
POLITICAL NEWS*B	-0.0574	0.010	-6.033	0.000
JUSTICE_AND_SECURITY_POLICY*I	-0.1287	0.021	-6.069	0.000
DEBATE*OE	-0.0477	0.006	-8.236	0.000
POLITICIAN_B*I	-0.0544	0.008	-6.867	0.000
GENERAL NEWS*AA	-0.0006	0.003	-0.202	0.840
POLITICAL NEWS*A	-0.0322	0.008	-4.032	0.000
POLITICIAN_A*I	-0.0480	0.007	-6.764	0.000
DEBATE*B	-0.0454	0.009	-5.175	0.000
TABLOID*C	-0.0630	0.006	-10.936	0.000
POLITICIAN_V*AA	-0.0692	0.011	-6.125	0.000
WOMEN_ALL*AA	-0.0103	0.005	-1.925	0.054
TABLOID*O	-0.0287	0.003	-10.673	0.000

POLITICIAN_I*OE	0.0065	0.009	0.711	0.477
LEFT LEANING NEWS*OE	-0.0190	0.005	-3.571	0.000
POLITICIAN_B*OE	0.0214	0.008	2.766	0.006
WOMEN_ALL*O	0.0735	0.003	22.664	0.000
LOCAL NEWS*OE	0.0298	0.006	5.093	0.000
HATE_PROBABILITY*V	-0.0492	0.004	-12.692	0.000
RIGHT LEANING NEWS*OE	0.0819	0.008	10.626	0.000
OTHER*B	-0.0442	0.008	-5.418	0.000
ECONOMY*B	0.2163	0.037	5.899	0.000
WOMEN_ALL*NB	0.0569	0.014	3.992	0.000
EDUCATION_AND_RESEARCH*I	0.1318	0.026	5.143	0.000
POLITICIAN_NB*B	-0.1429	0.030	-4.779	0.000
POLITICAL NEWS*AA	-0.0330	0.010	-3.257	0.001
POLITICIAN_F*I	-0.0439	0.008	-5.178	0.000
POLITICIAN_B*C	-0.0992	0.014	-7.167	0.000
LEFT LEANING NEWS*I	0.1036	0.011	9.309	0.000
POLITICIAN_NB*OE	-0.1257	0.030	-4.161	0.000
POLITICIAN_A*V	-0.0247	0.009	-2.619	0.009
POLITICIAN_I*O	0.1474	0.007	21.175	0.000
TABLOID*NB	-0.0352	0.009	-4.133	0.000
POLITICIAN_OE*V	-0.0401	0.012	-3.305	0.001
LEFT LEANING NEWS*O	0.1664	0.013	12.417	0.000
LEFT LEANING NEWS*V	0.1050	0.015	7.060	0.000

POLITICIAN_B*NB	-0.1188	0.029	-4.153	0.000
BY_WOMAN*O	0.0056	0.001	4.428	0.000
DEBATE*AA	-0.0357	0.009	-4.094	0.000
POLITICIAN_OE*O	0.0883	0.011	7.679	0.000
LEFT LEANING NEWS*NB	0.2694	0.063	4.274	0.000
LOCAL NEWS*O	-0.0078	0.004	-2.019	0.043
REFUGEES_AND_INTEGRATION*C	0.2505	0.034	7.378	0.000
EDUCATION_AND_RESEARCH*B	0.1502	0.035	4.284	0.000
POLITICAL NEWS*C	0.0979	0.021	4.768	0.000
POLITICIAN_B*A	0.0486	0.009	5.586	0.000
POLITICIAN_AA*I	0.1039	0.014	7.243	0.000
POLITICIAN_V*C	0.0479	0.011	4.312	0.000
POLITICIAN_AA*O	0.1196	0.015	8.046	0.000
POLITICIAN_OE*A	0.0425	0.008	5.122	0.000
RIGHT LEANING NEWS*V	-0.0176	0.005	-3.615	0.000
POLITICIAN_AA*V	0.0951	0.019	4.903	0.000
POLITICIAN_F*A	0.0274	0.007	4.017	0.000
RIGHT LEANING NEWS*I	-0.0148	0.006	-2.429	0.015
POLITICIAN_V*I	0.0984	0.007	14.424	0.000
POLITICIAN_A*O	0.0975	0.010	9.822	0.000
POLITICIAN_I*V	0.0610	0.008	7.829	0.000
POLITICAL NEWS*I	0.0797	0.011	7.364	0.000
POLITICIAN_C*A	0.0340	0.012	2.946	0.003

POLITICIAN_AA*A	0.0578	0.013	4.372	0.000
GENERAL NEWS*REFUGEES_AND_INTEGRATION*O	-0.2426	0.013	-18.283	0.000
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*O	0.0572	0.021	2.772	0.006
GENERAL NEWS*REFUGEES_AND_INTEGRATION*V	-0.2258	0.020	-11.290	0.000
GENERAL NEWS*HEALTH*O	0.2360	0.031	7.691	0.000
TABLOID*HEALTH*O	0.1346	0.039	3.438	0.001
TABLOID*JUSTICE_AND_SECURITY_POLICY*I	-0.1228	0.036	-3.434	0.001
TABLOID*JUSTICE_AND_SECURITY_POLICY*O	0.0786	0.020	3.871	0.000
TABLOID*HEALTH*I	-0.2274	0.064	-3.567	0.000
GENERAL NEWS*RELIGION*O	-0.0723	0.014	-5.355	0.000
WOMEN_ALL*RELIGION*B	-0.0822	0.036	-2.304	0.021
WOMEN_ALL*POLITICAL_GAMES_AND_REFERENDUMS*O	-0.0850	0.038	-2.216	0.027
POLITICIAN_V*ECONOMY*A	-0.2633	0.056	-4.697	0.000
GENERAL NEWS*SOCIAL_POLICY*O	0.1916	0.032	5.952	0.000
HATE_PROBABILITY*ECONOMY*O	0.2731	0.060	4.533	0.000
WOMEN_ALL*ECONOMY*O	-0.4147	0.063	-6.625	0.000
POLITICIAN_I*ECONOMY*I	0.1201	0.035	3.395	0.001
POLITICIAN_F*REFUGEES_AND_INTEGRATION*O	-0.1811	0.032	-5.640	0.000
POLITICIAN_I*ECONOMY*OE	-0.3777	0.074	-5.078	0.000
POLITICIAN_A*ECONOMY*V	-0.4081	0.111	-3.660	0.000
POLITICIAN_A*ECONOMY*OE	0.2969	0.091	3.258	0.001
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*OE	-0.8563	0.183	-4.689	0.000
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*V	0.3443	0.102	3.364	0.001

POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*B	-0.7275	0.204	-3.559	0.000
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*AA	-0.3713	0.150	-2.473	0.013
GENERAL NEWS*DOMESTIC_POLICY*C	-0.2339	0.075	-3.102	0.002
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*C	0.9360	0.209	4.482	0.000
GENERAL NEWS*DOMESTIC_POLICY*O	0.1066	0.024	4.436	0.000
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*I	0.6312	0.152	4.142	0.000
HATE_PROBABILITY*RELIGION*A	0.1308	0.033	3.934	0.000
GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY*OE	-0.0103	0.025	-0.418	0.676
GENERAL NEWS*RELIGION*I	0.2072	0.033	6.317	0.000
WOMEN_ALL*RELIGION*V	0.1392	0.027	5.242	0.000
HATE_PROBABILITY*RELIGION*I	-0.0874	0.038	-2.311	0.021
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*C	-0.3673	0.088	-4.187	0.000
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*I	-0.1201	0.041	-2.928	0.003
GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY*O	0.1250	0.018	7.029	0.000
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.2939	0.039	7.491	0.000
POLITICIAN_B*ECONOMY*B	-0.3897	0.099	-3.935	0.000
WOMEN_ALL*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*OE	-0.2216	0.051	-4.387	0.000
DEBATE*RELIGION*I	0.4017	0.095	4.226	0.000
POLITICIAN_V*FOREIGN_POLICY*B	1.8741	0.338	5.544	0.000
POLITICIAN_V*FOREIGN_POLICY*A	0.9598	0.221	4.337	0.000
POLITICIAN_V*FOREIGN_POLICY*AA	1.1762	0.288	4.086	0.000
POLITICIAN_V*FOREIGN_POLICY*OE	0.5062	0.202	2.501	0.012
TABLOID*REFUGEES_AND_INTEGRATION*O	-0.1970	0.028	-7.067	0.000

POLITICIAN_OE*POLITICAL_GAMES_AND_REFERENDUMS*C	2.0126	0.508	3.964	0.000
POLITICIAN_F*DOMESTIC_POLICY*O	-0.2884	0.080	-3.618	0.000
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*O	-0.1066	0.039	-2.704	0.007
LOCAL NEWS*REFUGEES_AND_INTEGRATION*I	0.2751	0.072	3.802	0.000
POLITICIAN_V*RELIGION*B	0.0788	0.030	2.632	0.008
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*AA	0.4761	0.121	3.938	0.000
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*OE	0.6489	0.086	7.565	0.000
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*B	0.3559	0.136	2.625	0.009
POLITICIAN_V*RELIGION*I	-0.1489	0.031	-4.769	0.000
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*I	-0.2826	0.063	-4.475	0.000
POLITICIAN_V*HEALTH*V	-0.2318	0.069	-3.351	0.001
POLITICIAN_C*CLIMATE_AND_ENVIRONMENT*A	0.4518	0.103	4.395	0.000
POLITICIAN_OE*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.2980	0.071	4.193	0.000
POLITICIAN_B*FOREIGN_POLICY*OE	0.5468	0.154	3.546	0.000
POLITICAL NEWS*ECONOMY*O	0.6890	0.130	5.315	0.000
POLITICAL NEWS*ECONOMY*V	0.7362	0.165	4.465	0.000
POLITICIAN_C*EMPLOYMENT_AND_THE_LABOR_MARKET*OE	-0.6533	0.168	-3.892	0.000
POLITICAL NEWS*DOMESTIC_POLICY*NB	2.4647	0.529	4.657	0.000
POLITICAL NEWS*DOMESTIC_POLICY*O	0.8149	0.134	6.060	0.000
POLITICIAN_C*FOREIGN_POLICY*AA	-1.9349	0.434	-4.462	0.000
POLITICIAN_V*TECHNOLOGY_AND_DIGITALIZATION*A	1.0104	0.160	6.304	0.000
OTHER*CULTURE*I	-0.8378	0.233	-3.595	0.000
TABLOID*RELIGION*I	0.1386	0.035	3.933	0.000

DEBATE*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.6703	0.127	5.277	0.000
TABLOID*POLITICAL_GAMES_AND_REFERENDUMS*O	-0.3091	0.069	-4.486	0.000
RIGHT LEANING NEWS*ECONOMY*OE	-0.1364	0.157	-0.871	0.384
POLITICIAN_A*RELIGION*V	0.2719	0.065	4.178	0.000
GENERAL NEWS*ECONOMY*O	0.3333	0.037	9.023	0.000
POLITICIAN_C*JUSTICE_AND_SECURITY_POLICY*OE	0.3511	0.092	3.797	0.000
GENERAL NEWS*ECONOMY*V	0.1390	0.060	2.299	0.022
RIGHT LEANING NEWS*DOMESTIC_POLICY*V	-0.2992	0.070	-4.285	0.000
TABLOID*HATE_PROBABILITY	0.0103	0.003	3.274	0.001
GENERAL NEWS*HATE_PROBABILITY	-0.0253	0.003	-9.366	0.000
WOMEN_ALL*I*HATE_PROBABILITY	-0.0432	0.009	-4.594	0.000
POLITICAL NEWS*REFUGEES_AND_INTEGRATION*HATE_PROBABILITY	-0.3788	0.097	-3.916	0.000
GENERAL NEWS*POLITICAL_GAMES_AND_REFERENDUMS*HATE_PROBABILITY	0.2063	0.056	3.705	0.000
GENERAL NEWS*A*HATE_PROBABILITY	0.0293	0.006	4.566	0.000
TABLOID*REFUGEES_AND_INTEGRATION*O*HATE_PROBABILITY	0.1839	0.045	4.063	0.000
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET*O*HATE_PROBABILITY	0.3118	0.081	3.844	0.000
POLITICIAN_OE*O*HATE_PROBABILITY	-0.1138	0.025	-4.577	0.000
WOMEN_ALL*RELIGION*V*HATE_PROBABILITY	-0.2128	0.052	-4.092	0.000
O*EDUCATION_AND_RESEARCH*HATE_PROBABILITY	-0.2326	0.070	-3.330	0.001
RIGHT LEANING NEWS*ECONOMY*OE*HATE_PROBABILITY	-2.6375	0.516	-5.114	0.000
POLITICIAN_A*O*HATE_PROBABILITY	-0.0924	0.025	-3.763	0.000
RIGHT LEANING NEWS*HATE_PROBABILITY	0.0376	0.005	6.849	0.000
GENERAL NEWS*RELIGION*I*HATE_PROBABILITY	-0.2868	0.074	-3.878	0.000

RIGHT LEANING NEWS*REFUGEES_AND_INTEGRATION*HATE_PROBABILITY	-0.1126	0.031	-3.601	0.000
POLITICIAN_V*FOREIGN_POLICY*B*HATE_PROBABILITY	-1.9434	0.470	-4.139	0.000
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*B*HATE_PROBABILITY	1.2377	0.317	3.904	0.000
GENERAL NEWS*ECONOMY*V*HATE_PROBABILITY	0.3297	0.192	1.714	0.086
OMNIBUS:	5031.932	Durbin-Watson:	1.883	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	8710.193	
SKEW:	-0.051	Prob(JB):	0.00	
KURTOSIS:	3.685	Cond. No.	2.97e+09	

Appendix 8.4-SI Discussion Compression Function

```
def compress_discussion(x,length=55,mode='running'):
    if len(x) < length:
        while len(x) < length:
            idx = random.randint(2,len(x)-2)
            val = float(np.mean([x[idx-1],x[idx+1]]))
            x.insert(idx,val)
    elif len(x) > length:
        while len(x) > length:
            try:
                idx = random.randint(1,len(x)-3)
                val = float(np.mean([x.pop(idx),x.pop(idx+1)]))
                x.insert(idx,val)
            except:
                print (idx)
                print (len(x))
                sys.exit()
    else:
        pass
    if mode == 'cummulative':
        new_x = []
        for r in range(len(x)):
            new_x.append( np.mean(np.array(list(x[:r+1]))) )
        return new_x
    elif mode == 'running':
        new_x = []
        for r in range(len(x)):
            if r == range(len(x))[0]:
                new_x.append(np.mean(np.array(list([x[r],x[r+1],x[r+2]]))))
            elif r == range(len(x))[-1]:
                new_x.append(np.mean(np.array(list([x[r],x[r-1],x[r-2]]))))
            else:
                new_x.append(np.mean(np.array(list([x[r-1],x[r],x[r+1]]))))
        return new_x
    else:
        return x
```

Appendix 8.8-SIC

DEP. VARIABLE:	**HOMOGENITY_ALL**	**R-SQUARED:**	**0.294**	
MODEL:	OLS	Adj. R-squared:	0.293	
METHOD:	Least Squares	F-statistic:	1745.	
DATE:	Tue	15 Oct 2019	Prob (F-statistic):	0.00
TIME:	02:49:10	Log-Likelihood:	2.7158e+05	
NO. OBSERVATIONS:	239320	AIC:	-5.430e+05	
DF RESIDUALS:	239262	BIC:	-5.424e+05	
DF MODEL:	57			
COVARIANCE TYPE:	nonrobust			
	coef	**std err**	**t**	**P>|t|**
CONST	-0.2553	0.053	-4.772	0.000
REACTIONS_TOTAL^2	0.5729	0.048	11.999	0.000
REACTIONS_TOTAL	0.0718	0.073	0.979	0.328
REACTIONS_TOTAL^3	-0.2220	0.025	-8.908	0.000
WOMEN_ALL^2	-0.4482	0.023	-19.683	0.000
WOMEN_ALL^3	0.2131	0.014	14.816	0.000
WOMEN_ALL*COMMENTS_TOTAL	-0.5267	0.021	-24.906	0.000
REACTIONS_TOTAL*REFUGEES_AND_INTEGRATION	0.2102	0.013	15.793	0.000
COMMENTS_TOTAL*REACTIONS_TOTAL	-0.2684	0.070	-3.818	0.000
COMMENTS_TOTAL*REFUGEES_AND_INTEGRATION	0.9164	0.046	20.031	0.000
REFUGEES_AND_INTEGRATION	-0.6750	0.048	-13.975	0.000
WOMEN_ALL	0.8833	0.024	37.566	0.000
WOMEN_ALL*REFUGEES_AND_INTEGRATION	-0.0710	0.013	-5.353	0.000
REACTIONS_TOTAL*POLITICAL_GAMES_AND_REFERENDUMS	0.5635	0.025	22.308	0.000
COMMENTS_TOTAL^3	-0.1210	0.056	-2.145	0.032
COMMENTS_TOTAL^2	0.3661	0.108	3.380	0.001

POLITICAL_GAMES_AND_REFERENDUMS	-0.3541	0.023	-15.316	0.000
REACTIONS_TOTAL*RELIGION	-0.0078	0.014	-0.565	0.572
WOMEN_ALL*POLITICAL_GAMES_AND_REFERENDUMS	0.5774	0.027	21.534	0.000
RELIGION	0.1334	0.011	12.008	0.000
REACTIONS_TOTAL*TECHNOLOGY_AND_DIGITALIZATION	-0.0454	0.026	-1.713	0.087
JUSTICE_AND_SECURITY_POLICY*REFUGEES_AND_INTEGRATION	0.1130	0.017	6.565	0.000
JUSTICE_AND_SECURITY_POLICY*TECHNOLOGY_AND_DIGITALIZATION	0.4152	0.041	10.192	0.000
TECHNOLOGY_AND_DIGITALIZATION*RELIGION	0.4645	0.033	14.247	0.000
WOMEN_ALL*SAD_TOTAL	0.2018	0.013	15.660	0.000
ANGER_AND_HARSHNESS*REFUGEES_AND_INTEGRATION	0.0002	1.06e-05	17.109	0.000
SAD_TOTAL*COMMENTS_TOTAL	0.0162	0.065	0.249	0.803
SAD_TOTAL	-0.0605	0.068	-0.885	0.376
TECHNOLOGY_AND_DIGITALIZATION	0.1674	0.122	1.369	0.171
REACTIONS_TOTAL*JUSTICE_AND_SECURITY_POLICY	0.0289	0.016	1.817	0.069
COMMENTS_TOTAL*TECHNOLOGY_AND_DIGITALIZATION	0.3268	0.117	2.794	0.005
REACTIONS_TOTAL*ECONOMY	0.1109	0.009	11.975	0.000
SAD_TOTAL*REACTIONS_TOTAL	-0.1907	0.020	-9.312	0.000
REFUGEES_AND_INTEGRATION*TECHNOLOGY_AND_DIGITALIZATION	0.9600	0.033	29.125	0.000
REFUGEES_AND_INTEGRATION^2	-0.3242	0.006	-51.715	0.000
LOVE_TOTAL*REFUGEES_AND_INTEGRATION	-0.2292	0.069	-3.343	0.001
WOMEN_ALL*REACTIONS_TOTAL	-0.2561	0.006	-42.463	0.000
ANGER_AND_HARSHNESS*TECHNOLOGY_AND_DIGITALIZATION	0.0003	2.69e-05	12.095	0.000
JUSTICE_AND_SECURITY_POLICY	-0.3168	0.062	-5.092	0.000

COMMENTS_TOTAL*JUSTICE_AND_SECURITY_POLICY	0.4756	0.059	8.040	0.000
SAD_TOTAL^2	0.0737	0.010	7.120	0.000
REFUGEES_AND_INTEGRATION*RELIGION	-0.0942	0.014	-6.592	0.000
REFUGEES_AND_INTEGRATION*POLITICAL_GAMES_AND_REFERENDUMS	-0.0485	0.031	-1.591	0.112
WOMEN_ALL*ECONOMY	0.0633	0.015	4.325	0.000
DOMESTIC_POLICY*REFUGEES_AND_INTEGRATION	0.0830	0.024	3.519	0.000
REACTIONS_TOTAL*FOREIGN_POLICY	0.1192	0.007	18.165	0.000
SHARES*REFUGEES_AND_INTEGRATION	-1.569e-05	5.37e-06	-2.923	0.003
JUSTICE_AND_SECURITY_POLICY*RELIGION	-0.1117	0.012	-9.292	0.000
ANGER_AND_HARSHNESS*RELIGION	0.0002	9.54e-06	16.837	0.000
JUSTICE_AND_SECURITY_POLICY^2	-0.1030	0.012	-8.286	0.000
LOVE_TOTAL*SAD_TOTAL	-0.4135	0.084	-4.898	0.000
FOREIGN_POLICY*TECHNOLOGY_AND_DIGITALIZATION	0.6113	0.093	6.542	0.000
REFUGEES_AND_INTEGRATION*EMPLOYMENT_AND_THE_LABOR_MARKET	0.2078	0.034	6.114	0.000
LOVE_TOTAL*POLITICAL_GAMES_AND_REFERENDUMS	0.2951	0.126	2.338	0.019
POLITICAL_GAMES_AND_REFERENDUMS*TECHNOLOGY_AND_DIGITALIZATION	-0.4867	0.096	-5.065	0.000
FOREIGN_POLICY*REFUGEES_AND_INTEGRATION	0.1237	0.021	5.972	0.000
RELIGION^2	-0.0371	0.005	-7.985	0.000
COMMENTS_TOTAL*HEALTH	0.2264	0.060	3.742	0.000
HEALTH	-0.1913	0.058	-3.308	0.001
ECONOMY*POLITICAL_GAMES_AND_REFERENDUMS	-0.0981	0.040	-2.433	0.015
REACTIONS_TOTAL*CLIMATE_AND_ENVIRONMENT	-0.0962	0.012	-7.716	0.000
REACTIONS_TOTAL*DOMESTIC_POLICY	-0.0631	0.017	-3.746	0.000

DOMESTIC_POLICY*RELIGION	0.2434	0.030	8.163	0.000
ECONOMY^2	-0.0756	0.015	-4.994	0.000
WOMEN_ALL*LOVE_TOTAL	0.3722	0.022	17.071	0.000
POLITICAL_GAMES_AND_REFERENDUMS*RELIGION	-0.1445	0.032	-4.546	0.000
ANGER_AND_HARSHNESS*JUSTICE_AND_SECURITY_POLICY	0.0001	1.05e-05	13.418	0.000
WOMEN_ALL*JUSTICE_AND_SECURITY_POLICY	-0.1027	0.012	-8.352	0.000
WOMEN_ALL*CLIMATE_AND_ENVIRONMENT	0.3075	0.024	12.896	0.000
POLITICAL_GAMES_AND_REFERENDUMS*HEALTH	0.2503	0.063	3.961	0.000
LOVE_TOTAL*RELIGION	-0.5107	0.062	-8.277	0.000
SAD_TOTAL*JUSTICE_AND_SECURITY_POLICY	-0.1121	0.020	-5.517	0.000
WOMEN_ALL*TECHNOLOGY_AND_DIGITALIZATION	-0.3217	0.021	-15.666	0.000
REFUGEES_AND_INTEGRATION*EDUCATION_AND_RESEARCH	-0.3402	0.051	-6.640	0.000
POLITICAL_GAMES_AND_REFERENDUMS^2	-0.4385	0.024	-18.478	0.000
ECONOMY*REFUGEES_AND_INTEGRATION	-0.0336	0.021	-1.600	0.110
REACTIONS_TOTAL*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.1176	0.021	-5.699	0.000
DOMESTIC_POLICY	0.0800	0.014	5.802	0.000
LOVE_TOTAL*CLIMATE_AND_ENVIRONMENT	0.8844	0.138	6.430	0.000
SOCIAL_POLICY*RELIGION	0.0396	0.051	0.779	0.436
SAD_TOTAL*ANGER_AND_HARSHNESS	-0.0001	1.17e-05	-11.180	0.000
SAD_TOTAL*TECHNOLOGY_AND_DIGITALIZATION	0.4906	0.085	5.774	0.000
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*RELIGION	-0.0108	0.030	-0.361	0.718
WOMEN_ALL*SHARES	-6.038e-06	1.19e-06	-5.088	0.000
JUSTICE_AND_SECURITY_POLICY^3	0.0286	0.006	5.022	0.000

POLITICAL_GAMES_AND_REFERENDUMS*SOCIAL_POLICY	-0.5440	0.053	-10.228	0.000
FOREIGN_POLICY^2	-0.0803	0.010	-8.191	0.000
SHARES*FOREIGN_POLICY	0.0001	1.81e-05	5.756	0.000
CLIMATE_AND_ENVIRONMENT*REFUGEES_AND_INTEGRATION	-0.4647	0.064	-7.293	0.000
DOMESTIC_POLICY*JUSTICE_AND_SECURITY_POLICY	-0.1234	0.028	-4.378	0.000
DOMESTIC_POLICY^2	-0.0166	0.005	-3.379	0.001
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*TECHNOLOGY_AND_DIGITALIZATION	-0.8583	0.138	-6.210	0.000
CLIMATE_AND_ENVIRONMENT*POLITICAL_GAMES_AND_REFERENDUMS	-0.3811	0.054	-7.047	0.000
SHARES*HEALTH	-2.834e-05	1e-05	-2.832	0.005
ECONOMY*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.1277	0.027	-4.662	0.000
SHARES*POLITICAL_GAMES_AND_REFERENDUMS	-4.488e-05	1.69e-05	-2.657	0.008
EMPLOYMENT_AND_THE_LABOR_MARKET	0.0760	0.019	3.906	0.000
REFUGEES_AND_INTEGRATION^3	0.0560	0.002	36.584	0.000
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*REFUGEES_AND_INTEGRATION	-0.3603	0.038	-9.406	0.000
ECONOMY*TECHNOLOGY_AND_DIGITALIZATION	-0.8348	0.063	-13.217	0.000
JUSTICE_AND_SECURITY_POLICY*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	-0.2486	0.063	-3.938	0.000
CULTURE*EMPLOYMENT_AND_THE_LABOR_MARKET	0.3259	0.091	3.587	0.000
SHARES*JUSTICE_AND_SECURITY_POLICY	-5.153e-05	8.63e-06	-5.970	0.000
SAD_TOTAL*CULTURE	0.2294	0.051	4.477	0.000
SAD_TOTAL*SOCIAL_POLICY	-0.0629	0.041	-1.521	0.128
LOVE_TOTAL*COMMENTS_TOTAL	-0.4505	0.113	-3.971	0.000
ECONOMY^3	0.0252	0.007	3.433	0.001
CLIMATE_AND_ENVIRONMENT*RELIGION	-0.1631	0.053	-3.073	0.002

REACTIONS_TOTAL*EDUCATION_AND_RESEARCH	-0.0200	0.012	-1.730	0.084
LOVE_TOTAL	-0.0108	0.123	-0.088	0.930
CULTURE*SOCIAL_POLICY	0.0165	0.083	0.199	0.843
DOMESTIC_POLICY*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	0.1719	0.073	2.366	0.018
WOMEN_ALL*EVERYDAY_LIFE_AND_CONSUMPTION	0.0736	0.009	8.303	0.000
SOCIAL_POLICY*EDUCATION_AND_RESEARCH	-0.0019	0.063	-0.029	0.977
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*POLITICAL_GAMES_AND_REFERENDUMS	-0.5535	0.078	-7.067	0.000
SAD_TOTAL*REFUGEES_AND_INTEGRATION	-0.4800	0.031	-15.553	0.000
TECHNOLOGY_AND_DIGITALIZATION*EDUCATION_AND_RESEARCH	-0.5842	0.123	-4.747	0.000
CULTURE*TECHNOLOGY_AND_DIGITALIZATION	-0.4124	0.091	-4.529	0.000
SOCIAL_POLICY*HEALTH	0.1234	0.046	2.672	0.008
SAD_TOTAL*FOREIGN_POLICY	-0.2415	0.050	-4.786	0.000
SHARES*ECONOMY	-8.695e-05	1.24e-05	-6.992	0.000
LOVE_TOTAL^2	0.6687	0.078	8.608	0.000
TECHNOLOGY_AND_DIGITALIZATION^2	-0.2759	0.024	-11.415	0.000
SOCIAL_POLICY^2	-0.0233	0.007	-3.298	0.001
REACTIONS_TOTAL*SOCIAL_POLICY	-0.0485	0.024	-2.003	0.045
RELIGION^3	0.0037	0.001	5.030	0.000
ANGER_AND_HARSHNESS*POLITICAL_GAMES_AND_REFERENDUMS	-0.0001	3.57e-05	-4.006	0.000
WOMEN_ALL*EMPLOYMENT_AND_THE_LABOR_MARKET	0.1131	0.019	6.052	0.000
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION^2	0.1526	0.020	7.535	0.000
CULTURE*EVERYDAY_LIFE_AND_CONSUMPTION	0.2250	0.060	3.723	0.000
LOVE_TOTAL^3	-0.7208	0.092	-7.849	0.000

CLIMATE_AND_ENVIRONMENT*SOCIAL_POLICY	-0.5735	0.120	-4.788	0.000
LOVE_TOTAL*TECHNOLOGY_AND_DIGITALIZATION	-0.4334	0.136	-3.197	0.001
LOVE_TOTAL*ANGER_AND_HARSHNESS	-0.0001	1.44e-05	-7.873	0.000
CULTURE*HEALTH	0.1971	0.060	3.285	0.001
FOREIGN_POLICY*EVERYDAY_LIFE_AND_CONSUMPTION	-0.4096	0.082	-4.990	0.000
POLITICAL_GAMES_AND_REFERENDUMS^3	0.1351	0.008	16.456	0.000
CLIMATE_AND_ENVIRONMENT^3	0.0103	0.003	3.843	0.000
SOCIAL_POLICY	0.1363	0.020	6.669	0.000
JUSTICE_AND_SECURITY_POLICY*HEALTH	-0.1769	0.028	-6.253	0.000
ANGER_AND_HARSHNESS^2	-1.235e-08	5.05e-10	-24.423	0.000
ANGER_AND_HARSHNESS^3	6.441e-13	3.18e-14	20.231	0.000
LOVE_TOTAL*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	-0.6042	0.156	-3.885	0.000
ANGER_AND_HARSHNESS*DOMESTIC_POLICY	3.568e-05	1.56e-05	2.291	0.022
WOMEN_ALL*ANGER_AND_HARSHNESS	6.962e-05	3.32e-06	20.974	0.000
WOMEN_ALL*EDUCATION_AND_RESEARCH	0.0932	0.019	5.034	0.000
SHARES^3	7.291e-16	4.16e-16	1.752	0.080
ANGER_AND_HARSHNESS*CULTURE	7.126e-05	1.55e-05	4.610	0.000
ANGER_AND_HARSHNESS*ECONOMY	-0.0002	2.53e-05	-8.667	0.000
LOVE_TOTAL*REACTIONS_TOTAL	0.1315	0.042	3.128	0.002
TECHNOLOGY_AND_DIGITALIZATION^3	0.0185	0.005	4.110	0.000
SAD_TOTAL*POLITICAL_GAMES_AND_REFERENDUMS	-0.9453	0.098	-9.620	0.000
ANGER_AND_HARSHNESS*SOCIAL_POLICY	-3.764e-05	1.78e-05	-2.110	0.035
OMNIBUS:	46298.449	Durbin-Watson:	1.872	
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	97833.731	

SKEW:	1.141	Prob(JB):	0.00
KURTOSIS:	5.146	Cond. No.	5.21e+14

Appendix 8.12-SIC

OLS Regression Results

DEP. VARIABLE:	INITIAL_DISAGREE_ALL	R-SQUARED:	0.321	
MODEL:	OLS	Adj. R-squared:	0.320	
METHOD:	Least Squares	F-statistic:	829.5	
DATE:	Sat	19 Oct 2019	Prob (F-statistic):	0.00
TIME:	14:03:04	Log-Likelihood:	92812.	
NO. OBSERVATIONS:	98523	AIC:	-1.855e+05	
DF RESIDUALS:	98466	BIC:	-1.850e+05	
DF MODEL:	56			
COVARIANCE TYPE:	nonrobust			

	coef	std err	t	P>|t|	[0.025	0.975]
CONST	0.7372	0.053	13.993	0.000	0.634	0.840
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS	0.1749	0.004	47.781	0.000	0.168	0.182
WOMEN_COMMENTS^2	-0.2284	0.028	-8.085	0.000	-0.284	-0.173
WOMEN_COMMENTS	0.0829	0.011	7.257	0.000	0.061	0.105
HOMOGENITY_ALL	-0.1233	0.017	-7.198	0.000	-0.157	-0.090
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*B	0.5915	0.021	28.382	0.000	0.551	0.632
COMMENTS_TOTAL*POLITICAL NEWS	0.1059	0.006	17.386	0.000	0.094	0.118
AGG_HATE_PROBABILITY*POLITICAL NEWS	0.0635	0.014	4.501	0.000	0.036	0.091
WOMEN_COMMENTS^3	0.1298	0.020	6.427	0.000	0.090	0.169
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*POLITICAL NEWS	-0.1278	0.009	-14.260	0.000	-0.145	-0.110
WOMEN_COMMENTS*POLITICAL NEWS	0.0408	0.010	4.256	0.000	0.022	0.060
WOMEN_REACTIONS^3	-0.1276	0.031	-4.166	0.000	-0.188	-0.068
WOMEN_REACTIONS^2	0.2127	0.048	4.478	0.000	0.120	0.306
WOMEN_REACTIONS	-0.1560	0.023	-6.878	0.000	-0.200	-0.112
LOVE_TOTAL*POLITICAL NEWS	0.2658	0.038	7.071	0.000	0.192	0.339
AGG_HATE_PROBABILITY*B	-0.0190	0.018	-1.074	0.283	-0.054	0.016
LOVE_TOTAL	0.5720	0.023	25.199	0.000	0.527	0.616

B	-0.2218	0.015	-14.649	0.000	-0.251	-0.192
AGG_HATE_PROBABILITY	0.2093	0.012	17.863	0.000	0.186	0.232
HOMOGENITY_ALL*POLITICAL NEWS	-0.5914	0.048	-12.308	0.000	-0.686	-0.497
WOMEN_REACTIONS*B	0.0814	0.015	5.518	0.000	0.052	0.110
SAD_TOTAL	-0.5808	0.021	-27.330	0.000	-0.622	-0.539
WOMEN_COMMENTS*TABLOID	0.0185	0.012	1.536	0.125	-0.005	0.042
WOMEN_REACTIONS*TABLOID	0.0208	0.014	1.518	0.129	-0.006	0.048
TABLOID	-0.0729	0.009	-8.221	0.000	-0.090	-0.056
LOVE_TOTAL*GENERAL NEWS	0.2902	0.021	13.620	0.000	0.248	0.332
AGG_HATE_PROBABILITY^2	-0.2449	0.021	-11.806	0.000	-0.286	-0.204
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*F	0.7054	0.029	24.549	0.000	0.649	0.762
HOMOGENITY_ALL*TABLOID	0.1884	0.042	4.530	0.000	0.107	0.270
SAD_TOTAL^2	1.7051	0.104	16.432	0.000	1.502	1.909
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*TABLOID	0.0283	0.016	1.719	0.086	-0.004	0.061
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*A	0.6417	0.019	34.085	0.000	0.605	0.679
WOMEN_COMMENTS*B	0.0433	0.010	4.202	0.000	0.023	0.064
COMMENTS_TOTAL	-0.5380	0.064	-8.453	0.000	-0.663	-0.413
V	0.3727	0.032	11.653	0.000	0.310	0.435
COMMENTS_TOTAL^2	-0.4839	0.048	-10.124	0.000	-0.578	-0.390
COMMENTS_TOTAL^3	0.4963	0.060	8.321	0.000	0.379	0.613
COMMENTS_TOTAL*V	-0.0171	0.034	-0.495	0.621	-0.085	0.051
SAD_TOTAL^3	-1.4656	0.119	-12.272	0.000	-1.700	-1.232
HOMOGENITY_ALL*C	-0.9550	0.037	-25.585	0.000	-1.028	-0.882
HOMOGENITY_ALL*LEFT LEANING NEWS	-0.2888	0.091	-3.181	0.001	-0.467	-0.111
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*C	-1.0429	0.038	-27.207	0.000	-1.118	-0.968
WOMEN_COMMENTS*V	0.0370	0.008	4.679	0.000	0.022	0.053
WOMEN_COMMENTS*GENERAL NEWS	-0.0166	0.005	-3.169	0.002	-0.027	-0.006
AGG_HATE_PROBABILITY*V	-0.0399	0.016	-2.426	0.015	-0.072	-0.008
HOMOGENITY_ALL*O	-1.0219	0.036	-28.015	0.000	-1.093	-0.950
HOMOGENITY_ALL*I	-1.1775	0.039	-30.209	0.000	-1.254	-1.101
ANGRY_TOTAL*V	0.1339	0.037	3.585	0.000	0.061	0.207

ANGRY_TOTAL*A	-0.3452	0.026	-13.468	0.000	-0.395	-0.295
HOMOGENITY_ALL*AA	0.4351	0.075	5.835	0.000	0.289	0.581
HOMOGENITY_ALL*A	0.7159	0.062	11.571	0.000	0.595	0.837
SAD_TOTAL*A	-0.3272	0.058	-5.605	0.000	-0.442	-0.213
HATE_PROBABILITY	0.0755	0.010	7.833	0.000	0.057	0.094
COMMENTS_TOTAL*SPORT	-0.1005	0.013	-8.004	0.000	-0.125	-0.076
WOMEN_REACTIONS*LEFT LEANING NEWS	-0.0029	0.015	-0.191	0.848	-0.033	0.027
ANGRY_TOTAL^3	0.0995	0.053	1.891	0.059	-0.004	0.203
HOMOGENITY_ALL*FTF	-0.1989	0.054	-3.651	0.000	-0.306	-0.092
COMMENTS_TOTAL*LEFT LEANING NEWS	0.0055	0.019	0.288	0.773	-0.032	0.043
SAD_TOTAL*LOCAL NEWS	0.0778	0.015	5.166	0.000	0.048	0.107
LOVE_TOTAL*DEBATE	0.4587	0.070	6.518	0.000	0.321	0.597
AGG_HATE_PROBABILITY*LEFT LEANING NEWS	-0.1141	0.025	-4.654	0.000	-0.162	-0.066
AGG_HATE_PROBABILITY*GENERAL NEWS	0.0581	0.008	7.054	0.000	0.042	0.074
HOMOGENITY_ALL*B	0.3706	0.081	4.563	0.000	0.211	0.530
HOMOGENITY_ALL*LO	0.3126	0.098	3.205	0.001	0.121	0.504
NB	0.2998	0.014	21.042	0.000	0.272	0.328
AGG_HATE_PROBABILITY*F	-0.0986	0.022	-4.554	0.000	-0.141	-0.056
LOVE_TOTAL^2	-1.8337	0.151	-12.123	0.000	-2.130	-1.537
ANGRY_TOTAL^2	-0.2372	0.055	-4.321	0.000	-0.345	-0.130
WOMEN_COMMENTS*O	0.0412	0.016	2.605	0.009	0.010	0.072
ANGRY_TOTAL*OE	-0.4777	0.030	-15.820	0.000	-0.537	-0.418
WOMEN_REACTIONS*GENERAL NEWS	0.0086	0.006	1.490	0.136	-0.003	0.020
WOMEN_REACTIONS*C	0.0375	0.016	2.331	0.020	0.006	0.069
COMMENTS_TOTAL*LO	-0.1772	0.017	-10.449	0.000	-0.210	-0.144
COMMENTS_TOTAL*C	-0.1714	0.044	-3.937	0.000	-0.257	-0.086
WOMEN_REACTIONS*LO	0.0627	0.013	4.710	0.000	0.037	0.089
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*AA	0.5701	0.033	17.114	0.000	0.505	0.635
WOMEN_REACTIONS*O	-0.0026	0.024	-0.108	0.914	-0.050	0.045
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*O	-1.5223	0.083	-18.423	0.000	-1.684	-1.360
AGG_HATE_PROBABILITY*C	-0.0847	0.021	-4.095	0.000	-0.125	-0.044

C	0.4357	0.042	10.398	0.000	0.354	0.518
F	-0.2802	0.021	-13.632	0.000	-0.320	-0.240
SAD_TOTAL*F	-0.2630	0.065	-4.052	0.000	-0.390	-0.136
AGG_HATE_PROBABILITY*O	-0.0542	0.022	-2.450	0.014	-0.097	-0.011
WOMEN_REACTIONS*SPORT	0.0708	0.027	2.575	0.010	0.017	0.125
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*OE	0.4442	0.018	25.077	0.000	0.409	0.479
HOMOGENITY_ALL*GENERAL NEWS	0.0499	0.023	2.195	0.028	0.005	0.094
HOMOGENITY_ALL*RIGHT LEANING NEWS	-0.5709	0.033	-17.086	0.000	-0.636	-0.505
HATE_PROBABILITY*V	-0.0266	0.008	-3.350	0.001	-0.042	-0.011
HOMOGENITY_ALL*SPORT	0.3654	0.211	1.733	0.083	-0.048	0.779
SAD_TOTAL*B	-0.8474	0.061	-13.817	0.000	-0.968	-0.727
COMMENTS_TOTAL*O	0.1109	0.060	1.858	0.063	-0.006	0.228
LOVE_TOTAL*INFOTAINMENT	0.2391	0.053	4.479	0.000	0.134	0.344
O	0.3024	0.056	5.430	0.000	0.193	0.412
WOMEN_COMMENTS*OE	0.0549	0.012	4.643	0.000	0.032	0.078
WOMEN_REACTIONS*F	0.0525	0.018	2.994	0.003	0.018	0.087
LOVE_TOTAL*RIGHT LEANING NEWS	0.1265	0.065	1.957	0.050	-0.000	0.253
HATE_PROBABILITY^2	-0.1467	0.030	-4.903	0.000	-0.205	-0.088
SAD_TOTAL*KØBENHAVN KOMMUNE	-0.1315	0.043	-3.083	0.002	-0.215	-0.048
LOVE_TOTAL*V	0.0945	0.054	1.753	0.080	-0.011	0.200
WOMEN_COMMENTS*A	0.0321	0.008	4.158	0.000	0.017	0.047
LOVE_TOTAL*LEFT LEANING NEWS	-0.3654	0.099	-3.708	0.000	-0.559	-0.172
AGG_HATE_PROBABILITY*LOCAL NEWS	0.0247	0.008	3.142	0.002	0.009	0.040
COMMENTS_TOTAL*AA	0.1885	0.048	3.952	0.000	0.095	0.282
ANGRY_TOTAL*F	-0.4214	0.040	-10.612	0.000	-0.499	-0.344
WOMEN_REACTIONS*I	-0.1954	0.016	-12.341	0.000	-0.226	-0.164
AA	-0.3559	0.052	-6.857	0.000	-0.458	-0.254
LOVE_TOTAL*I	0.1632	0.055	2.983	0.003	0.056	0.270
SAD_TOTAL*INFOTAINMENT	0.0273	0.021	1.314	0.189	-0.013	0.068
HOMOGENITY_ALL*KØBENHAVN KOMMUNE	0.1996	0.085	2.351	0.019	0.033	0.366
HOMOGENITY_ALL*FREDERIKSBERG KOMMUNE	-0.5787	0.082	-7.029	0.000	-0.740	-0.417

COMMENTS_TOTAL*KØBENHAVN KOMMUNE	-0.0499	0.013	-3.975	0.000	-0.074	-0.025
ANGRY_TOTAL*DEBATE	0.1094	0.018	6.191	0.000	0.075	0.144
HATE_PROBABILITY*NB	-0.0641	0.017	-3.678	0.000	-0.098	-0.030
COMMENTS_TOTAL*OE	-0.1045	0.009	-11.943	0.000	-0.122	-0.087
HATE_PROBABILITY^3	0.0795	0.023	3.480	0.001	0.035	0.124
AGG_HATE_PROBABILITY*I	-0.0996	0.022	-4.462	0.000	-0.143	-0.056
WOMEN_REACTIONS*RIGHT LEANING NEWS	0.0240	0.013	1.876	0.061	-0.001	0.049
HOMOGENITY_ALL*NB	-0.7999	0.055	-14.640	0.000	-0.907	-0.693
RIGHT LEANING NEWS	0.4126	0.042	9.905	0.000	0.331	0.494
SHARES	-4.404e-06	1.17e-06	-3.770	0.000	-6.69e-06	-2.11e-06
COMMENTS_TOTAL*I	-0.2519	0.043	-5.801	0.000	-0.337	-0.167
GENERAL NEWS	-0.3757	0.023	-16.366	0.000	-0.421	-0.331
SAD_TOTAL*AA	-0.1434	0.052	-2.756	0.006	-0.245	-0.041
HOMOGENITY_ALL*F	0.6913	0.083	8.293	0.000	0.528	0.855
I	0.5201	0.042	12.262	0.000	0.437	0.603
LOVE_TOTAL*TABLOID	0.1495	0.031	4.839	0.000	0.089	0.210
AGG_HATE_PROBABILITY*INFOTAINMENT	0.0782	0.016	4.806	0.000	0.046	0.110
COMMENTS_TOTAL*GENERAL NEWS	0.3708	0.024	15.754	0.000	0.325	0.417
COMMENTS_TOTAL*RIGHT LEANING NEWS	-0.2741	0.046	-6.008	0.000	-0.364	-0.185
AGG_HATE_PROBABILITY*OE	-0.1296	0.022	-5.806	0.000	-0.173	-0.086
SAD_TOTAL*I	-0.7453	0.147	-5.069	0.000	-1.034	-0.457
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*RIGHT LEANING NEWS	-0.3867	0.020	-19.153	0.000	-0.426	-0.347
ANGRY_TOTAL*AA	-0.1781	0.047	-3.791	0.000	-0.270	-0.086
WOMEN_COMMENTS*DEBATE	-0.0224	0.006	-3.468	0.001	-0.035	-0.010
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*LO	0.2722	0.029	9.448	0.000	0.216	0.329
WOMEN_REACTIONS*FREDERIKSBERG KOMMUNE	-0.0710	0.034	-2.073	0.038	-0.138	-0.004
ANGRY_TOTAL	0.1257	0.014	8.817	0.000	0.098	0.154
INFOTAINMENT	-0.0130	0.004	-3.375	0.001	-0.021	-0.005
COMMENTS_TOTAL*FREDERIKSBERG KOMMUNE	0.1498	0.026	5.731	0.000	0.099	0.201
SHARES*A	-5.33e-06	2.95e-06	-1.807	0.071	-1.11e-05	4.53e-07

AGG_HATE_PROBABILITY*A	-0.1086	0.017	-6.225	0.000	-0.143	-0.074
ANGRY_TOTAL*B	-0.2522	0.045	-5.578	0.000	-0.341	-0.164
WOMEN_COMMENTS*F	0.0575	0.012	4.796	0.000	0.034	0.081
LOVE_TOTAL*A	-0.2525	0.065	-3.876	0.000	-0.380	-0.125
HATE_PROBABILITY*A	-0.0297	0.008	-3.532	0.000	-0.046	-0.013
ANGRY_TOTAL*INFOTAINMENT	0.0590	0.013	4.534	0.000	0.034	0.085
LOVE_TOTAL^3	1.1999	0.183	6.559	0.000	0.841	1.558
A	-0.2294	0.013	-18.165	0.000	-0.254	-0.205
ANGRY_TOTAL*GENERAL NEWS	0.0221	0.005	4.438	0.000	0.012	0.032
LOVE_TOTAL*O	0.3022	0.056	5.416	0.000	0.193	0.411
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*V	-1.3065	0.026	-49.430	0.000	-1.358	-1.255
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*LEFT LEANING NEWS	0.1895	0.027	7.113	0.000	0.137	0.242
LEFT_WING_COMMENTS_INV*LEFT_WING_REACTIONS*KØBENHAVN KOMMUNE	0.1251	0.029	4.374	0.000	0.069	0.181
HOMOGENITY_ALL*V	-1.1278	0.027	-41.582	0.000	-1.181	-1.075
SHARES^3	1.115e-15	5.89e-16	1.893	0.058	-3.97e-17	2.27e-15
OMNIBUS:	14517.273	Durbin-Watson:	1.872			
PROB(OMNIBUS):	0.000	Jarque-Bera (JB):	24668.320			
SKEW:	0.984	Prob(JB):	0.00			
KURTOSIS:	4.462	Cond. No.	8.35e+15			

Appendix 8.8-SIADJ

The table shows the adjusted coefficients for Figure 8.8. The coefficients are normalized by the mean of the values for the given variable it belongs to. Some variables are in the range 0 - ∞ while others are only 0 – 1. The normalization makes it easier to compare the importance of each coefficient to all coefficients in the same model. The adjusted coefficients are sorted based on their absolute value such that the strength of coefficients can be compared regardless of whether they are negative or positive.

PARAMETER	COEFFICIENT	ADJUSTED_COEFFICIENT
ANGER_AND_HARSHNESS	0.04950	0.64790
WOMEN_ALL	-0.08114	-0.40233
REFUGEES_AND_INTEGRATION	0.19610	0.05739
POLITICAL_GAMES_AND_REFERENDUMS	0.23889	0.03267
TECHNOLOGY_AND_DIGITALIZATION	0.24401	0.03260
SAD_TOTAL	-0.10560	-0.03028
COMMENTS_TOTAL	-0.00003	-0.03016
JUSTICE_AND_SECURITY_POLICY	0.07168	0.02650
REACTIONS_TOTAL	0.00000	0.01916
RELIGION	0.09200	0.01838
ECONOMY	0.09048	0.01765
SOCIAL_POLICY	0.08873	0.01100
EMPLOYMENT_AND_THE_LABOR_MARKET	0.05475	0.00686
FOREIGN_POLICY	0.06202	0.00639
DOMESTIC_POLICY	0.02513	0.00607
CLIMATE_AND_ENVIRONMENT	0.07431	0.00551
HEALTH	0.03145	0.00496
EDUCATION_AND_RESEARCH	0.04946	0.00487
EVERYDAY_LIFE_AND_CONSUMPTION	0.04698	0.00267
SHARES	0.00000	-0.00140

Appendix 8.12-SIADJ

The table shows the adjusted coefficients for Figure 8.12. The coefficients are normalized by the mean of the values for the given variable it belongs to. Some variables are in the range 0 - ∞ while others are only 0 – 1. The normalization makes it easier to compare the importance of each coefficient to all coefficients in the same model. The adjusted coefficients are sorted based on their absolute value such that the strength of coefficients can be compared regardless of whether they are negative or positive.

PARAMETER	COEFFICIENT	ADJUSTED_COEFFICIENT
COMMENTS_TOTAL	-0.35315	-0.33923
HOMOGENITY_ALL	-0.79889	-0.06938
WOMEN_ALL	-0.09663	-0.04541
LEFT_WING_ALL	-0.08240	-0.04404
AGG_HATE_PROBABILITY	0.12017	0.02363
LOVE_TOTAL	0.37174	0.00618
V	0.10244	0.00445
REFUGEES_AND_INTEGRATION	0.15990	0.00438
A	0.08589	0.00403
O	0.13116	0.00353
JUSTICE_AND_SECURITY_POLICY	-0.11507	-0.00346
SAD_TOTAL	-0.12411	-0.00322
B	0.10412	0.00311
F	0.10176	0.00265
POLITICAL NEWS	0.07378	0.00257
TABLOID	-0.02959	-0.00211
OE	0.07630	0.00207
AA	0.10473	0.00207
I	0.04852	0.00162
C	0.06195	0.00158
POLITICAL_GAMES_AND_REFERENDUMS	0.09785	0.00145
ANGRY_TOTAL	-0.02058	-0.00141
CULTURE	-0.09371	-0.00116
HEALTH	-0.08453	-0.00115
RIGHT LEANING NEWS	0.03382	0.00102
TECHNOLOGY_AND_DIGITALIZATION	-0.10971	-0.00100
ECONOMY	0.04181	0.00091
LEFT LEANING NEWS	0.04007	0.00083
LOCAL NEWS	-0.00743	-0.00056
GENERAL NEWS	0.00190	0.00056

NB	0.15529	0.00051
EDUCATION_AND_RESEARCH	-0.05187	-0.00050
RELIGION	0.02772	0.00048
SPORT	-0.09536	-0.00046
FREDERIKSBERG KOMMUNE	0.09092	0.00041
CLIMATE_AND_ENVIRONMENT	0.03284	0.00026
BUSINESS	-0.02529	-0.00011
BRØNDBY KOMMUNE	-0.11185	-0.00011
FTF	0.01353	0.00010
LIFESTYLE	-0.02274	-0.00010
DEBATE	0.00195	0.00004
RANDERS KOMMUNE	-0.06075	-0.00004
SILKEBORG KOMMUNE	-0.03189	-0.00003
OTHER	-0.00213	-0.00002
HØRSHOLM KOMMUNE	-0.06098	-0.00001
LO	-0.00058	-0.00001

Appendix 8.15-SIADJ

The table shows the adjusted coefficients for Figure 8.15. The coefficients are normalized by the mean of the values for the given variable it belongs to. Some variables are in the range 0 - ∞ while others are only 0 – 1. The normalization makes it easier to compare the importance of each coefficient to all coefficients in the same model. The adjusted coefficients are sorted based on their absolute value such that the strength of coefficients can be compared regardless of whether they are negative or positive.

PARAMETER	COEFFICIENT	ADJUSTED_COEFFICIENT
COMMENTS_TOTAL	-0.19024	-0.18585
REACTIONS_TOTAL	-0.04887	-0.03767
AGG_HATE_PROBABILITY	-0.15062	-0.03259
WOMEN_COMMENTS	0.07166	0.03244
REFUGEES_AND_INTEGRATION	-0.20427	-0.00629
ANGRY_TOTAL	0.04029	0.00389
O	-0.06966	-0.00332
JUSTICE_AND_SECURITY_POLICY	0.08570	0.00317
V	-0.08025	-0.00275
A	-0.08514	-0.00261
TABLOID	0.01890	0.00241
OE	-0.09536	-0.00218
POLITICAL_GAMES_AND_REFERENDUMS	-0.16733	-0.00216
LOVE_TOTAL	-0.13504	-0.00193
B	-0.11401	-0.00177
I	-0.06579	-0.00166
F	-0.08950	-0.00159
CULTURE	0.11824	0.00146
POLITICAL NEWS	-0.06363	-0.00137
RIGHT LEANING NEWS	-0.02201	-0.00134
HEALTH	0.09044	0.00132
AA	-0.07878	-0.00129
LEFT LEANING NEWS	-0.05804	-0.00128
TECHNOLOGY_AND_DIGITALIZATION	0.10295	0.00116
LOCAL NEWS	0.01820	0.00116
EMPLOYMENT_AND_THE_LABOR_MARKET	0.08214	0.00095
DOMESTIC_POLICY	0.03467	0.00073
EDUCATION_AND_RESEARCH	0.08544	0.00072
ECONOMY	-0.03859	-0.00060
SAD_TOTAL	0.01893	0.00056

RELIGION	-0.02443	-0.00051
INFOTAINMENT	0.01290	0.00038
GENERAL NEWS	0.00114	0.00038
CLIMATE_AND_ENVIRONMENT	-0.05627	-0.00033
DEBATE	-0.01830	-0.00032
SPORT	0.08656	0.00028
FREDERIKSBERG KOMMUNE	-0.06632	-0.00027
LO	0.03346	0.00027
NB	-0.09425	-0.00024
C	-0.01484	-0.00022
FTF	-0.02352	-0.00020
BRØNDBY KOMMUNE	0.10965	0.00012
CHARITY	0.05120	0.00005
RANDERS KOMMUNE	0.11176	0.00003
RINGKØBINGSKJERN KOMMUNE	0.07623	0.00003
AABENRAA KOMMUNE	-0.05479	0.00000

Appendix 8.3-SICADJ

The table shows the adjusted coefficients for Appendix 8.3-SI. The coefficients are normalized by the mean of the values for the given variable it belongs to. Some variables are in the range 0 - ∞ while others are only 0 – 1. The normalization makes it easier to compare the importance of each coefficient to all coefficients in the same model. The adjusted coefficients are sorted based on their absolute value such that the strength of coefficients can be compared regardless of whether they are negative or positive.

PARAMETER	COEFFICIENT	ADJUSTED_COEFFICIENT
O	-0.04839	-0.01575
WOMEN_ALL*O	0.07354	0.01247
TABLOID	0.05958	0.01089
JUSTICE_AND_SECURITY_POLICY	0.25397	0.00912
REFUGEES_AND_INTEGRATION	-0.17011	-0.00671
HATE_PROBABILITY*O	-0.06140	-0.00641
MESSAGE_LEN	0.00000	0.00563
WOMEN_ALL*V	0.07780	0.00419
WOMEN_ALL*I	0.12923	0.00418
POLITICIAN_V	-0.11367	-0.00405
GENERAL NEWS	0.00877	0.00390
WOMEN_ALL	0.00643	0.00329
GENERAL NEWS*REFUGEES_AND_INTEGRATION	-0.22396	-0.00288
O*JUSTICE_AND_SECURITY_POLICY	-0.18957	-0.00276
GENERAL NEWS*HATE_PROBABILITY	-0.02530	-0.00273
I	-0.03266	-0.00273
WOMEN_ALL*JUSTICE_AND_SECURITY_POLICY	-0.13747	-0.00234
TABLOID*O	-0.02871	-0.00231
HATE_PROBABILITY	-0.00861	-0.00221
HEALTH	0.16117	0.00210
B	-0.03199	-0.00206
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION	0.14210	0.00183
CULTURE	0.15510	0.00178
OE	-0.01271	-0.00178
POLITICIAN_B	-0.10530	-0.00158
AA	0.03114	0.00148
POLITICIAN_I	-0.06592	-0.00137
BY_WOMAN	-0.00308	-0.00137
HATE_PROBABILITY*V	-0.04920	-0.00131
ECONOMY	-0.12025	-0.00129

V	-0.01145	-0.00124
GENERAL NEWS*REFUGEES_AND_INTEGRATION*O	-0.24256	-0.00116
LOCAL NEWS	0.03765	0.00114
GENERAL NEWS*RELIGION	-0.12710	-0.00111
GENERAL NEWS*POLITICAL_GAMES_AND_REFERENDUMS	-0.33016	-0.00111
POLITICIAN_OE	-0.07297	-0.00110
POLITICIAN_A	-0.05975	-0.00109
GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY	0.08207	0.00108
TABLOID*V	-0.04819	-0.00101
GENERAL NEWS*A	0.01517	0.00099
HATE_PROBABILITY*JUSTICE_AND_SECURITY_POLICY	0.09260	0.00098
POLITICAL NEWS	-0.08821	-0.00097
EMPLOYMENT_AND_THE_LABOR_MARKET	-0.08408	-0.00093
TECHNOLOGY_AND_DIGITALIZATION	0.09501	0.00092
WOMEN_ALL*RELIGION	-0.06532	-0.00091
WOMEN_ALL*SOCIAL_POLICY	0.12634	0.00090
DEBATE	-0.06159	-0.00089
POLITICIAN_F	-0.05368	-0.00088
BY_WOMAN*O	0.00558	0.00084
WOMEN_ALL*CULTURE	-0.12764	-0.00077
WOMEN_ALL*C	0.07977	0.00077
GENERAL NEWS*I	0.02106	0.00077
A	0.00544	0.00074
A*REFUGEES_AND_INTEGRATION	0.20893	0.00074
TABLOID*OE	0.03725	0.00071
POLITICIAN_V*O	0.05588	0.00070
GENERAL NEWS*HEALTH	0.12358	0.00069
HATE_PROBABILITY*RELIGION	0.06823	0.00066
O*ECONOMY	0.28943	0.00066
RIGHT LEANING NEWS*HATE_PROBABILITY	0.03759	0.00064
FOREIGN_POLICY	0.07500	0.00063
GENERAL NEWS*FOREIGN_POLICY	-0.14391	-0.00062
POLITICAL_GAMES_AND_REFERENDUMS	-0.06102	-0.00061
V*JUSTICE_AND_SECURITY_POLICY	-0.15801	-0.00061
TABLOID*REFUGEES_AND_INTEGRATION	-0.15174	-0.00061
TABLOID*RELIGION	-0.15953	-0.00060
WOMEN_ALL*B	0.01849	0.00058
RELIGION	-0.02004	-0.00058
WOMEN_ALL*A	-0.00767	-0.00058
POLITICIAN_AA	-0.07042	-0.00057
SOCIAL_POLICY	-0.05206	-0.00056
C	0.02568	0.00053
RIGHT LEANING NEWS*REFUGEES_AND_INTEGRATION	0.12937	0.00053
TABLOID*HATE_PROBABILITY	0.01032	0.00053

GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY*O	0.12501	0.00050
HATE_PROBABILITY*B	-0.03313	-0.00049
WOMEN_ALL*GENDER_EQUALITY_GENDER_AND_DISCRIMINATIO N	-0.17996	-0.00046
O*FOREIGN_POLICY	-0.14616	-0.00046
I*REFUGEES_AND_INTEGRATION	0.19509	0.00046
WOMEN_ALL*ECONOMY*O	-0.41466	-0.00044
O*EMPLOYMENT_AND_THE_LABOR_MARKET	0.14140	0.00042
GENERAL NEWS*A*HATE_PROBABILITY	0.02932	0.00041
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*O	0.05715	0.00041
TABLOID*REFUGEES_AND_INTEGRATION*O	-0.19697	-0.00040
TABLOID*A	0.01626	0.00040
WOMEN_ALL*HEALTH	-0.04612	-0.00038
DOMESTIC_POLICY	0.02378	0.00038
GENERAL NEWS*B	-0.01177	-0.00038
O*REFUGEES_AND_INTEGRATION	-0.02015	-0.00038
GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	0.07158	0.00037
POLITICIAN_C	-0.03993	-0.00037
GENERAL NEWS*DOMESTIC_POLICY	0.06881	0.00037
JUSTICE_AND_SECURITY_POLICY*I	-0.12865	-0.00036
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY	0.22406	0.00034
GENERAL NEWS*REFUGEES_AND_INTEGRATION*V	-0.22582	-0.00034
GENERAL NEWS*CULTURE	0.07797	0.00033
GENERAL NEWS*SOCIAL_POLICY	0.08593	0.00031
A*JUSTICE_AND_SECURITY_POLICY	-0.07967	-0.00031
POLITICIAN_V*I	0.09840	0.00031
LEFT LEANING NEWS	-0.02385	-0.00031
WOMEN_ALL*I*HATE_PROBABILITY	-0.04317	-0.00031
TABLOID*JUSTICE_AND_SECURITY_POLICY*O	0.07856	0.00030
GENERAL NEWS*HEALTH*O	0.23598	0.00030
I*ECONOMY	-0.15487	-0.00030
EDUCATION_AND_RESEARCH	0.04412	0.00029
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.29389	0.00028
POLITICIAN_I*O	0.14744	0.00028
O*EDUCATION_AND_RESEARCH	0.19712	0.00028
HATE_PROBABILITY*DOMESTIC_POLICY	0.07513	0.00027
POLITICIAN_NB	-0.16975	-0.00027
HATE_PROBABILITY*EMPLOYMENT_AND_THE_LABOR_MARKET	0.09586	0.00026
HATE_PROBABILITY*ECONOMY	-0.11596	-0.00026
OE*JUSTICE_AND_SECURITY_POLICY	-0.06462	-0.00026
WITH_LINK	-0.02056	-0.00026
WOMEN_ALL*AA	-0.01033	-0.00025
POLITICIAN_B*O	-0.11251	-0.00022
GENERAL NEWS*ECONOMY*O	0.33334	0.00022

I*RELIGION	0.10392	0.00022
WOMEN_ALL*POLITICAL_GAMES_AND_REFERENDUMS	-0.04843	-0.00022
RIGHT LEANING NEWS*A	0.09304	0.00022
V*POLITICAL_GAMES_AND_REFERENDUMS	-0.20536	-0.00022
C*JUSTICE_AND_SECURITY_POLICY	-0.26936	-0.00021
A*POLITICAL_GAMES_AND_REFERENDUMS	-0.15757	-0.00021
WOMEN_ALL*ECONOMY	-0.04901	-0.00021
LOCAL NEWS*REFUGEES_AND_INTEGRATION	-0.20570	-0.00020
SPORT	0.10643	0.00020
BY_WOMAN*RELIGION	-0.01673	-0.00020
RIGHT LEANING NEWS*REFUGEES_AND_INTEGRATION*HATE_PROBABILITY	-0.11258	-0.00020
TABLOID*C	-0.06302	-0.00020
LOCAL NEWS*A	0.03458	0.00019
POLITICIAN_V*OE	-0.08289	-0.00019
GENERAL NEWS*POLITICAL_GAMES_AND_REFERENDUMS*HATE_PROBABILITY	0.20631	0.00019
A*HEALTH	-0.09047	-0.00019
GENERAL NEWS*RELIGION*O	-0.07231	-0.00018
WOMEN_ALL*RELIGION*V	0.13916	0.00018
B*JUSTICE_AND_SECURITY_POLICY	-0.07557	-0.00018
TABLOID*FOREIGN_POLICY	-0.21757	-0.00018
A*RELIGION	0.06829	0.00018
HATE_PROBABILITY*ECONOMY*O	0.27312	0.00017
RIGHT LEANING NEWS	-0.00385	-0.00017
OE*FOREIGN_POLICY	0.16921	0.00017
GENERAL NEWS*SOCIAL_POLICY*O	0.19161	0.00017
POLITICIAN_A*O	0.09749	0.00016
OTHER*REFUGEES_AND_INTEGRATION	-0.47229	-0.00016
WOMEN_ALL*NB	0.05689	0.00016
V*REFUGEES_AND_INTEGRATION	0.04028	0.00016
TABLOID*REFUGEES_AND_INTEGRATION*O*HATE_PROBABILITY	0.18386	0.00015
LO	0.05600	0.00015
POLITICIAN_V*B	-0.08203	-0.00015
DEBATE*OE	-0.04774	-0.00015
POLITICIAN_V*A	-0.04929	-0.00015
GENERAL NEWS*DOMESTIC_POLICY*O	0.10658	0.00015
OE*REFUGEES_AND_INTEGRATION	0.03587	0.00014
O*CLIMATE_AND_ENVIRONMENT	0.24730	0.00014
B*REFUGEES_AND_INTEGRATION	-0.05445	-0.00014
TABLOID*POLITICAL_GAMES_AND_REFERENDUMS	-0.21300	-0.00014
GENERAL NEWS*RELIGION*I	0.20717	0.00014
AA*JUSTICE_AND_SECURITY_POLICY	-0.11415	-0.00014
REFUGEES_AND_INTEGRATION*C	0.25052	0.00014

POLITICIAN_B*V	-0.10984	-0.00014
V*EMPLOYMENT_AND_THE_LABOR_MARKET	0.15105	0.00013
TABLOID*HEALTH*O	0.13465	0.00013
POLITICIAN_OE*O	0.08827	0.00013
V*HEALTH	0.10380	0.00013
POLITICIAN_V*TECHNOLOGY_AND_DIGITALIZATION	0.28852	0.00013
OE*ECONOMY	0.08080	0.00013
CLIMATE_AND_ENVIRONMENT	-0.03207	-0.00013
RIGHT LEANING NEWS*OE	0.08185	0.00012
ECONOMY*B	0.21634	0.00012
WOMEN_ALL*RELIGION*B	-0.08221	-0.00012
WOMEN_ALL*POLITICAL_GAMES_AND_REFERENDUMS*O	-0.08503	-0.00012
TABLOID*EMPLOYMENT_AND_THE_LABOR_MARKET	0.08933	0.00011
NB	0.01634	0.00011
LIFESTYLE	0.05534	0.00011
POLITICAL NEWS*OE	-0.05815	-0.00011
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET	0.02489	0.00011
O*RELIGION	0.00921	0.00011
V*EDUCATION_AND_RESEARCH	0.15699	0.00010
POLITICIAN_I*ECONOMY*I	0.12010	0.00010
EDUCATION_AND_RESEARCH*I	0.13178	0.00010
OE*DOMESTIC_POLICY	-0.04245	-0.00010
HATE_PROBABILITY*RELIGION*A	0.13080	0.00010
POLITICIAN_I*V	0.06102	0.00009
O*EDUCATION_AND_RESEARCH*HATE_PROBABILITY	-0.23256	-0.00009
POLITICIAN_B*I	-0.05444	-0.00009
POLITICIAN_A*I	-0.04797	-0.00009
WOMEN_ALL*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION*OE	-0.22164	-0.00009
WOMEN_ALL*RELIGION*V*HATE_PROBABILITY	-0.21275	-0.00009
OE*CULTURE	0.06087	0.00009
LEFT LEANING NEWS*OE	-0.01897	-0.00009
TABLOID*POLITICAL_GAMES_AND_REFERENDUMS*O	-0.30912	-0.00009
NB*JUSTICE_AND_SECURITY_POLICY	-0.25251	-0.00009
GENERAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET*O*HATE_PROBABILITY	0.31185	0.00009
DEBATE*POLITICAL_GAMES_AND_REFERENDUMS	0.35370	0.00008
LOCAL NEWS*OE	0.02980	0.00008
LOCAL NEWS*O	-0.00778	-0.00008
POLITICIAN_B*POLITICAL_GAMES_AND_REFERENDUMS	0.21614	0.00008
POLITICAL NEWS*REFUGEES_AND_INTEGRATION	-0.17579	-0.00008
POLITICIAN_V*RELIGION	0.04881	0.00008
RIGHT LEANING NEWS*V	-0.01758	-0.00008
AA*HEALTH	-0.08982	-0.00008

POLITICIAN_A*EMPLOYMENT_AND_THE_LABOR_MARKET	0.13787	0.00008
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*I	-0.12013	-0.00008
POLITICIAN_I*ECONOMY	0.05137	0.00008
TABLOID*AA	0.02093	0.00008
TABLOID*ECONOMY	0.12835	0.00008
V*CLIMATE_AND_ENVIRONMENT	-0.16057	-0.00007
LEFT LEANING NEWS*O	0.16637	0.00007
POLITICIAN_B*ECONOMY	0.31351	0.00007
POLITICIAN_OE*POLITICAL_GAMES_AND_REFERENDUMS	0.14200	0.00007
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT	-0.29201	-0.00007
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*O	-0.10663	-0.00007
B*EMPLOYMENT_AND_THE_LABOR_MARKET	0.18030	0.00007
EDUCATION_AND_RESEARCH*B	0.15019	0.00007
LEFT LEANING NEWS*I	0.10359	0.00007
OTHER*POLITICAL_GAMES_AND_REFERENDUMS	-0.74402	-0.00007
DEBATE*RELIGION	-0.16977	-0.00007
HATE_PROBABILITY*A	0.00216	0.00007
I*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.07815	-0.00006
B*HEALTH	0.07899	0.00006
V*SOCIAL_POLICY	0.06756	0.00006
AA*EMPLOYMENT_AND_THE_LABOR_MARKET	0.10838	0.00006
AA*REFUGEES_AND_INTEGRATION	0.04625	0.00006
POLITICAL NEWS*B	-0.05737	-0.00006
TABLOID*JUSTICE_AND_SECURITY_POLICY*I	-0.12284	-0.00006
AA*DOMESTIC_POLICY	-0.06923	-0.00006
V*FOREIGN_POLICY	-0.06720	-0.00006
LOCAL NEWS*RELIGION	-0.23134	-0.00006
POLITICIAN_B*A	0.04858	0.00006
POLITICAL NEWS*I	0.07968	0.00006
TABLOID*JUSTICE_AND_SECURITY_POLICY	-0.00757	-0.00006
B*TECHNOLOGY_AND_DIGITALIZATION	0.11928	0.00006
GENERAL NEWS*RELIGION*I*HATE_PROBABILITY	-0.28680	-0.00006
POLITICIAN_V*AA	-0.06920	-0.00006
OTHER*B	-0.04419	-0.00006
POLITICIAN_C*CLIMATE_AND_ENVIRONMENT	-0.31098	-0.00006
POLITICAL NEWS*A	-0.03224	-0.00006
POLITICIAN_OE*O*HATE_PROBABILITY	-0.11383	-0.00006
POLITICIAN_OE*EMPLOYMENT_AND_THE_LABOR_MARKET	0.08382	0.00006
B*SOCIAL_POLICY	0.10394	0.00006
HATE_PROBABILITY*REFUGEES_AND_INTEGRATION*C	-0.36735	-0.00006
POLITICIAN_B*REFUGEES_AND_INTEGRATION	-0.03606	-0.00006
POLITICIAN_A*ECONOMY	-0.09172	-0.00006
HATE_PROBABILITY*RELIGION*I	-0.08741	-0.00006
POLITICIAN_F*A	0.02740	0.00006

A*SOCIAL_POLICY	-0.02939	-0.00005
POLITICIAN_OE*A	0.04248	0.00005
POLITICIAN_F*I	-0.04392	-0.00005
POLITICAL NEWS*REFUGEES_AND_INTEGRATION*HATE_PROBABILITY	-0.37879	-0.00005
DEBATE*B	-0.04540	-0.00005
C*RELIGION	0.09254	0.00005
C*DOMESTIC_POLICY	0.13284	0.00005
TABLOID*HEALTH	-0.02053	-0.00005
TABLOID*NB	-0.03519	-0.00005
DEBATE*JUSTICE_AND_SECURITY_POLICY	0.29724	0.00005
AA*ECONOMY	0.07256	0.00005
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*I	-0.28263	-0.00005
POLITICIAN_OE*JUSTICE_AND_SECURITY_POLICY	-0.08915	-0.00005
DEBATE*HEALTH	0.62011	0.00005
POLITICIAN_C*TECHNOLOGY_AND_DIGITALIZATION	-0.79097	-0.00005
NB*REFUGEES_AND_INTEGRATION	-0.12294	-0.00004
POLITICIAN_A*O*HATE_PROBABILITY	-0.09242	-0.00004
POLITICIAN_B*C	-0.09921	-0.00004
OTHER*DOMESTIC_POLICY	0.31805	0.00004
DEBATE*AA	-0.03569	-0.00004
GENERAL NEWS*ECONOMY*V	0.13905	0.00004
POLITICIAN_AA*O	0.11955	0.00004
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*OE	0.64893	0.00004
POLITICAL NEWS*EMPLOYMENT_AND_THE_LABOR_MARKET	0.41118	0.00004
POLITICIAN_F*REFUGEES_AND_INTEGRATION*O	-0.18110	-0.00004
POLITICIAN_AA*I	0.10391	0.00004
POLITICIAN_B*OE	0.02142	0.00004
O*HEALTH	0.01142	0.00004
POLITICIAN_C*JUSTICE_AND_SECURITY_POLICY	0.05749	0.00004
RIGHT LEANING NEWS*I	-0.01478	-0.00004
DEBATE*EDUCATION_AND_RESEARCH	0.44493	0.00004
POLITICIAN_A*EDUCATION_AND_RESEARCH	0.15948	0.00004
AA*CLIMATE_AND_ENVIRONMENT	-0.07456	-0.00004
LEFT LEANING NEWS*V	0.10497	0.00004
POLITICIAN_I*ECONOMY*OE	-0.37766	-0.00004
OTHER	0.00359	0.00004
LOCAL NEWS*ECONOMY	0.21692	0.00004
O*SOCIAL_POLICY	0.01132	0.00004
TABLOID*HEALTH*I	-0.22742	-0.00003
POLITICIAN_V*C	0.04791	0.00003
RIGHT LEANING NEWS*DOMESTIC_POLICY*V	-0.29924	-0.00003
WITH_LINK*FOREIGN_POLICY	0.21747	0.00003
POLITICIAN_V*ECONOMY*A	-0.26328	-0.00003

LEFT LEANING NEWS*REFUGEES_AND_INTEGRATION	-0.08256	-0.00003
DEBATE*GENDER_EQUALITY_GENDER_AND_DISCRIMINATION	0.28087	0.00003
POLITICAL NEWS*AA	-0.03302	-0.00003
POLITICIAN_A*V	-0.02470	-0.00003
POLITICAL NEWS*HEALTH	0.52489	0.00003
POLITICIAN_I*FOREIGN_POLICY	-0.24090	-0.00003
TABLOID*RELIGION*I	0.13863	0.00003
POLITICIAN_B*FOREIGN_POLICY	0.14851	0.00003
POLITICIAN_F*DOMESTIC_POLICY	-0.07429	-0.00003
POLITICIAN_B*ECONOMY*B	-0.38971	-0.00003
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*V	0.34429	0.00003
POLITICIAN_A*RELIGION	0.05898	0.00003
POLITICAL NEWS*ECONOMY	0.12930	0.00003
RIGHT LEANING NEWS*DOMESTIC_POLICY	-0.03732	-0.00003
POLITICIAN_NB*JUSTICE_AND_SECURITY_POLICY	0.36087	0.00003
NB*ECONOMY	0.61257	0.00003
DEBATE*TECHNOLOGY_AND_DIGITALIZATION	0.43373	0.00003
GENERAL NEWS*DOMESTIC_POLICY*C	-0.23388	-0.00003
NB*FOREIGN_POLICY	-0.29211	-0.00003
POLITICIAN_AA*A	0.05777	0.00003
A*ECONOMY	-0.01610	-0.00003
B*RELIGION	0.00811	0.00002
POLITICIAN_V*HEALTH*V	-0.23183	-0.00002
RIGHT LEANING NEWS*CLIMATE_AND_ENVIRONMENT	-0.38727	-0.00002
POLITICIAN_V*TECHNOLOGY_AND_DIGITALIZATION*A	1.01042	0.00002
POLITICIAN_V*FOREIGN_POLICY*B	1.87414	0.00002
POLITICAL NEWS*DOMESTIC_POLICY*O	0.81489	0.00002
OTHER*CULTURE	-0.27236	-0.00002
POLITICIAN_C*A	0.03400	0.00002
RIGHT LEANING NEWS*HEALTH	-0.08856	-0.00002
POLITICIAN_V*ECONOMY	0.02492	0.00002
POLITICIAN_V*DOMESTIC_POLICY	0.02724	0.00002
DEBATE*SOCIAL_POLICY	0.28967	0.00002
POLITICIAN_OE*V	-0.04008	-0.00002
B*POLITICAL_GAMES_AND_REFERENDUMS	0.03117	0.00002
C*CLIMATE_AND_ENVIRONMENT	0.18261	0.00002
POLITICIAN_V*RELIGION*I	-0.14891	-0.00002
POLITICAL NEWS*ECONOMY*O	0.68902	0.00002
POLITICIAN_NB*RELIGION	0.10461	0.00002
DEBATE*EMPLOYMENT_AND_THE_LABOR_MARKET	0.10648	0.00002
GENERAL NEWS*JUSTICE_AND_SECURITY_POLICY*OE	-0.01026	-0.00002
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*B*HATE_PROBABILITY	1.23767	0.00002
POLITICIAN_AA*EMPLOYMENT_AND_THE_LABOR_MARKET	0.12666	0.00002

POLITICIAN_F*REFUGEES_AND_INTEGRATION	0.01776	0.00002
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*B	0.35593	0.00002
POLITICIAN_A*ECONOMY*V	-0.40808	-0.00002
DEBATE*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.67027	0.00002
POLITICIAN_AA*V	0.09510	0.00002
NB*HEALTH	0.34070	0.00002
POLITICAL NEWS*DOMESTIC_POLICY	0.09193	0.00002
POLITICIAN_A*ECONOMY*OE	0.29686	0.00002
GENERAL NEWS*ECONOMY*V*HATE_PROBABILITY	0.32973	0.00002
POLITICAL NEWS*C	0.09786	0.00002
POLITICIAN_C*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.14163	-0.00002
POLITICIAN_OE*EMPLOYMENT_AND_THE_LABOR_MARKET*O	0.29803	0.00002
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*OE	-0.85625	-0.00002
OTHER*SOCIAL_POLICY	0.25982	0.00002
POLITICIAN_F*DOMESTIC_POLICY*O	-0.28839	-0.00002
RIGHT LEANING NEWS*ECONOMY*OE*HATE_PROBABILITY	-2.63751	-0.00002
POLITICIAN_V*FOREIGN_POLICY*A	0.95976	0.00002
GENERAL NEWS*AA	-0.00064	-0.00002
NB*EMPLOYMENT_AND_THE_LABOR_MARKET	0.39494	0.00001
I*CLIMATE_AND_ENVIRONMENT	-0.03660	-0.00001
POLITICIAN_C*GENDER_EQUALITY_GENDER_AND_DISCRIMINATIO N	-0.51274	-0.00001
GENERAL NEWS*ECONOMY	-0.00465	-0.00001
POLITICIAN_C*JUSTICE_AND_SECURITY_POLICY*OE	0.35111	0.00001
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*I	0.63117	0.00001
LOCAL NEWS*REFUGEES_AND_INTEGRATION*I	0.27506	0.00001
POLITICIAN_NB*B	-0.14287	-0.00001
POLITICIAN_C*FOREIGN_POLICY	-0.23565	-0.00001
POLITICIAN_B*FOREIGN_POLICY*OE	0.54675	0.00001
POLITICIAN_V*JUSTICE_AND_SECURITY_POLICY*AA	0.47613	0.00001
POLITICIAN_C*EMPLOYMENT_AND_THE_LABOR_MARKET*OE	-0.65329	-0.00001
OTHER*CULTURE*I	-0.83784	-0.00001
POLITICAL NEWS*ECONOMY*V	0.73618	0.00001
POLITICIAN_B*NB	-0.11884	-0.00001
POLITICIAN_V*RELIGION*B	0.07879	0.00001
POLITICIAN_NB*OE	-0.12571	-0.00001
OE*RELIGION	0.00337	0.00001
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*B	-0.72752	-0.00001
POLITICIAN_NB*HEALTH	1.09345	0.00001
DEBATE*RELIGION*I	0.40166	0.00001
POLITICIAN_C*CLIMATE_AND_ENVIRONMENT*A	0.45180	0.00001
POLITICIAN_V*EMPLOYMENT_AND_THE_LABOR_MARKET	-0.01918	-0.00001
POLITICIAN_I*OE	0.00647	0.00001
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*AA	-0.37125	-0.00001

POLITICIAN_V*FOREIGN_POLICY*AA	1.17623	0.00001
POLITICIAN_A*RELIGION*V	0.27190	0.00001
POLITICIAN_V*CLIMATE_AND_ENVIRONMENT*C	0.93599	0.00001
POLITICIAN_V*FOREIGN_POLICY*B*HATE_PROBABILITY	-1.94338	-0.00001
POLITICIAN_V*HEALTH	-0.02312	-0.00001
POLITICIAN_OE*POLITICAL_GAMES_AND_REFERENDUMS*C	2.01258	0.00001
V*ECONOMY	0.00527	0.00001
POLITICIAN_V*FOREIGN_POLICY*OE	0.50624	0.00001
POLITICIAN_C*FOREIGN_POLICY*AA	-1.93485	-0.00001
LEFT LEANING NEWS*NB	0.26937	0.00000
POLITICAL NEWS*DOMESTIC_POLICY*NB	2.46473	0.00000
RIGHT LEANING NEWS*ECONOMY*OE	-0.13639	0.00000
POLITICIAN_V*FOREIGN_POLICY	-0.00996	0.00000
RIGHT LEANING NEWS*ECONOMY	-0.00533	0.00000